ASSESSING PLANS THAT SUPPORT URBAN ADAPTATION TO CHANGING CLIMATE AND EXTREME EVENTS ACROSS SPATIAL SCALES

by

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B.A., University of Nairobi, 1997
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AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Environmental Design and Planning
College of Architecture, Planning and Design

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2015

Abstract

Despite the growing number of urban adaptation planning initiatives to climate change hazards, there exist significant barriers related to implementation uncertainties that hinder translation of adaptation plans into actions, resulting in a widely recognized 'planning-implementation gap' across scales and regions. Bridging the planning-implementation gap will require overcoming implementation uncertainties by better understanding the relationships between the primary factors driving adaptation planning initiatives and emerging adaptation options across spatial scales.

The modified Driver-Pressure-State-Impact-Response model published by Rounsevell, Dawson, and Harrison in 2010 provided a robust framework for identifying the primary factors driving adaptation planning initiatives and the emerging adaptation options related to risk of changing climate and flooding events in the urban context. Drawing on evidence from the systematic review of 121 adaptation planning case studies across North America, this research derived qualitative and quantitative data, which was subsequently analyzed using binary logistic regression to generate objective and generalizable findings.

The findings of binary logistic regression models suggest that the choice of specific adaptation options (namely enhancing adaptive capacity; management and conservation; and improving urban infrastructure, planning, and development) may be predicted based on the assessment of primary factors driving adaptation planning initiatives (namely, anticipation of economic benefits; perceived threats to management and conservation of urban natural resources; support of human and social systems; and improvement of policy and regulations) in relation to the risk of changing climate and urban flooding events. This does not imply that other primary factors (namely information and knowledge; perceived funding and economic opportunities; evidence of climate change effects; and general concerns) have no or insignificant relationships with the selection of adaptation options, only that the review did not find evidence to support such claims.

These study findings may offer useful guidance to the design and further development of planning and decision support tools that could be used for assessment of adaptation plans and selection of robust adaptation options that take account of uncertainties surrounding implementation of effective climate adaptation actions. Study findings can also inform evidence-based policy and investment decision making, especially in regions where urban adaptation plans are weak or absent.

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This dissertation would not have been possible without the support of my family, my fiancée Rose, and daughter Yonne.

Most of all, I thank God, who is able to do immeasurably more than all I ask or imagine.

Dedication

To

Mum and Dad,

Brothers and Sisters

Lovely Fiancée Rose,

Daughter Yonne

and

Friends

Chapter 1 - Introduction

Evidence is overwhelming that the earth's climate is warming and changing human and ecological systems around the globe (IPCC, 2012). Increasing frequency and magnitude of extreme events (e.g. drought and flooding) coupled with population growth, demographic structure and change, human migration, economic dynamics, land use change, and societal behavior are among the conspicuous changes that pose great challenges to planning, design, and policy decision-making in essentially every nation (Carmin et al. 2012b; Fussel, 2007; IPCC, 2012).

Urban environments are particularly vulnerable due to concentrations of people, built infrastructure, property investments, and services (Bulkeley and Tuts, 2013). The need for urban adaptation has become inevitable across all regions to reduce the impacts of changing climate (e.g. sea-level rise) and extreme flood events such as Superstorm Sandy's destruction to coastal urban infrastructure in New Jersey and New York in 2012 (Berrang-Ford, 2011; Bierbaum et al. 2012; Ford et al. 2011; Fussel, 2007).

Emerging adaptation planning research combined with advances in planning support systems (PSS) offer new possibilities for understanding, anticipating, and responding to the current and potential effects of changing climate (e.g. sea-level rise) and extreme events (e.g. drought and flooding) on urban land use, water quality, built infrastructure, and public health across spatial and temporal scales (Bierbaum et al. 2012; Preston, 2013). The evolution of PSS—an integrated system combining a range of databases, models, and visualization tools —represent a primary strategy to connect planning and decision-making and prepare cities to respond effectively to changing climate and extreme events (see e.g. Batty, 2008; Chakraborty et al. 2012; Drummond and French, 2008; Geertman and Stillwell 2009; Klosterman and Pettit, 2005; Nedovic`-Budic`, 2000; Vonk and Geertman, 2008).

In a number of regions and cities adaptation is beginning to take place at interlinking scales and consists of incremental rather than transformational adjustments to reduce vulnerability[1] and enhance the adaptive capacity[2] of natural systems, the built environment, and human populations to climate change and extreme events that involve severe flooding and drought (Carmin et al. 2012b; Fussel, 2007; IPCC, 2007; Kates et al. 2012). Though evidence shows similarities in approaches ('top-down' or 'bottom-up')[3] to design and implementation of adaptation planning initiatives, multiple qualitative and quantitative methods (e.g. scenario development and cost-benefit analysis) and tools (e.g. frameworks, models, and visualization tools) have been used to 1) understand climate vulnerability, 2) identify and evaluate adaptation response options, and 3) generate measures and strategies that can be implemented (including green infrastructure projects now burgeoning in many cities) at a variety of scales (Bierbaum et al. 2012; Carmin et al. 2012a; Kirshen et al. 2012).

Based on a global survey conducted in 2011 on urban climate adaptation planning, 68 percent of surveyed cities worldwide were engaged in some form of adaptation planning initiatives (Carmin et al. 2012b). This included 59 percent of surveyed cities in U.S. regions and 80 percent of surveyed cities in Africa regions (Carmin et al. 2012b). Examples of adaptation initiatives in the U.S. include the following communities: Keene, New Hampshire; New York City, New York; Seattle (King County), Washington; and Chicago, Illinois (Bierbaum et al. 2012). Each of these communities have designed and generated climate adaptation response options, and are in the process of implementing specific adaptation measures such as green building and ecologically based infrastructure that is predominantly decentralized and integrated with natural functions and settings (Bierbaum et al. 2012). It emerges that urban adaptation response options now common in practice include green infrastructure interventions, protection of coastal cities to effects of sea-level rise, flood insurance investments, and diversification and integration of climate adaptation plans into mainstream policies (IPCC, 2007; Karl et al. 2009).

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[1] Vulnerability is the context of uncertainty in which adaptation takes place, "the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including variability and extremes" (IPCC, 2007).

[2] Adaptive capacity is the ability or potential of a system to respond successfully to change, in order to reduce adverse impacts and take advantage of new opportunities (IPCC, 2007; Kates et al. 2012).

[3] The 'top-down' (impact-based) approaches consider climate risks, vulnerabilities, and impacts as the basis for adaptation planning while the 'bottom-up' (capacity-based) approaches employ participatory approaches, are place-based and scenario development forms the basis for the evaluation of these approaches (Bierbaum et al. 2012; Dessai and Hulme, 2004; Wilby and Dessai, 2010).

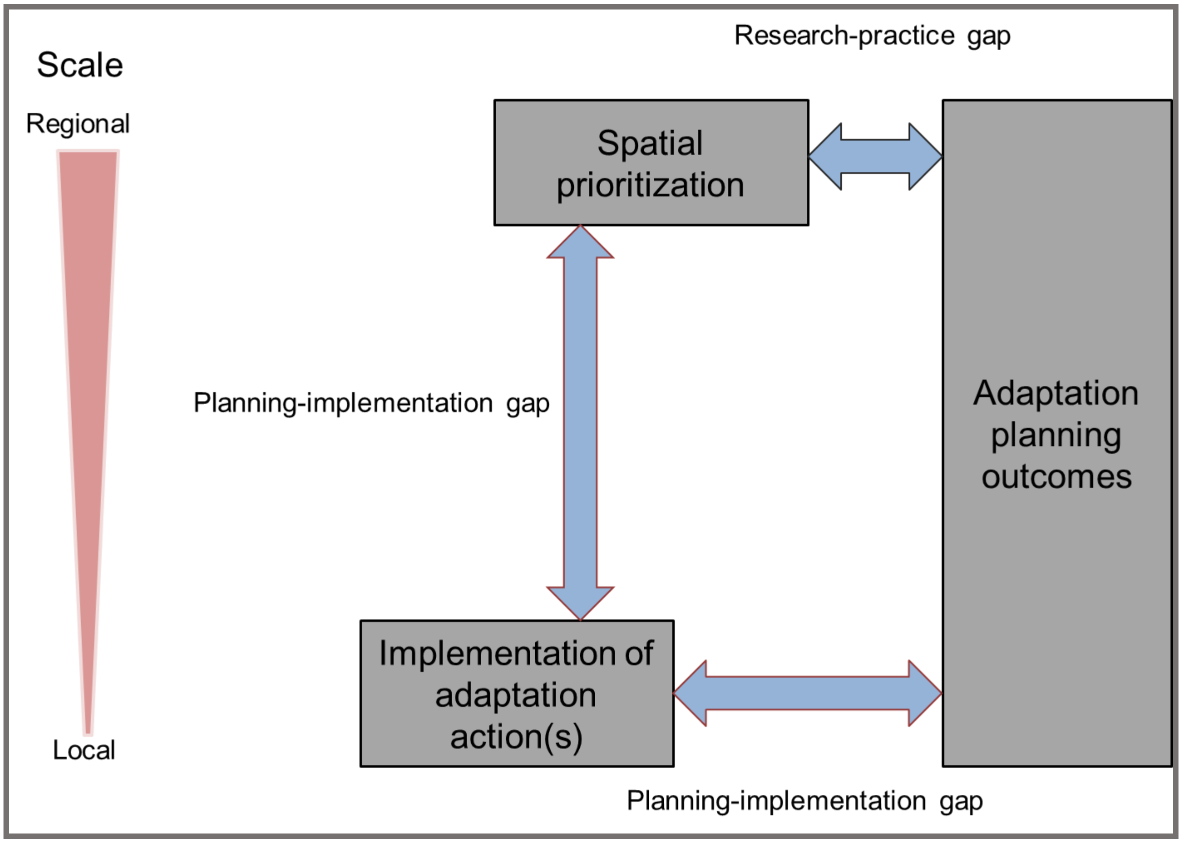
1.1 Problem description

Urban adaptation planning has been increasingly acknowledged to offer new possibilities for responding to the current and potential effects of changing climate (e.g. sea-level rise) and extreme events (e.g. drought and flooding) in regards to land use, built infrastructure, water quality, and public health across different scales (Berrang-Ford et al. 2010; Bierbaum et al. 2012; Carmin et al. 2012b; Ford et al. 2011; Hallegate and Corfee-Morlot, 2011). Nevertheless, despite the growing number of urban adaptation planning initiatives, there exists a widely recognized 'planning-implementation gap' that can be attributed to barriers (e.g. information and knowledge, funding, policy and regulations, and uncertainties) that continues to impede the effective implementation of adaptation options across a range of scales (Bierbaum et al. 2012; Biesbroek et al. 2013; Gagnon-Lebrun and Agrawala, 2007; Lehmann et al. 2013; Moser and Ekstrom, 2010).

Planning-implementation gaps occur when there is failure to translate the outcomes of a planning process into effective and beneficial actions (Knight et al. 2006). In adaptation planning practices, the planning-implementation gap (Figure 1.1) emerges as the divide between the spatial prioritization and the process of design, development, and selection of adaptation options and the implementation of selected adaptation options (Knight et al. 2006; Mills, 2011). In other words, the implementation gap manifests as the failure to translate the designed, developed, and selected robust and flexible adaptation options into adaptation actions across a range of spatial scales.

Studies that examine general trends related to climate adaptation planning initiatives in cities (e.g. Anguelovski and Carmin, 2011; Carmin et al. 2009; Poyar and Beller-Simms, 2010), suggest that having a good understanding about the drivers of adaptation planning (especially those associated with variations in the decision to select particular adaptation options over others), is the bottom line to reducing implementation uncertainties of adaptation options and subsequently bridging the planning-implementation gap across a range of scales and regions. Carmin et al. (2009) identified incentives (such as perceived risks to assets and property, economic benefits, funding, and policy and regulation), information (especially hard data), and resources (capacity) as the primary drivers of adaptation planning in cities.

Figure 1.1: A schematic of the three phases[4] of adaptation process and gaps[5] analysis



Source: Modified from Mills, 2011.

While the primary drivers of urban adaptation planning have been recognized, there is still limited insight into the association between the primary driving factors and the selection of adaptation options (such as enhancing urban adaptive capacity, natural resource management and conservation, improving infrastructure planning, and urban governance) that operate across a range of scales and regions (Biesbroek et al. 2010; Carmin et al. 2012a; Hallegate and Corfee-Morlot, 2011; Poyar and Beller-Simms, 2010).

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[4] The three main phases of adaptation process represented by the grey boxes include; (1) undertaking research to understand and define the problem, (2) planning process that entails developing, assessing, and selecting options for implementation, (3) implementation of selected adaptation options across a range of scales and context.

[5] The blue arrows between the phases represent the gaps that together make up the broader knowing-doing gaps (Pfeffer and Sutton, 1999). The focus narrows from research undertaking to implementation of actions.

Literature shows that adaptation planning initiatives are mostly reported in the form of case studies or project reports (Bierbaum et al. 2012; Biesbroek et al. 2013; Carmin et al. 2012a; Rounsevell et al, 2010). Much of the documentation that exists is in “grey” (non-peer-reviewed) literature, such as government reports and planning documents; agency “white” papers; and “expressions of interest” for consideration in national climate assessment reports (Bierbaum et al. 2012; Mastrandrea et al. 2010; Plummer and Armitage, 2010). The individuality of adaptation planning case studies also pose critical challenge to generalizability of outcomes (Garg et al. 2008). Individual adaptation planning cases are normally characterized with subjectivity in relation to their scope and geographic coverage, motivating factors, diversity of planning methods, approaches and tools used, and outcomes (UNFCCC, 2012). According to Garg et al. (2008), knowledge development is partly influenced by combining data from multiple primary studies of acceptable quality, and drawing from a larger context to provide generalizable findings with greater explanatory power, making lessons learned from these studies useable for planning and policy decision making.

1.2 Goal and research questions

This dissertation focuses on bridging the ‘planning-implementation gap’ of adaptation initiatives related to changing climate and extreme weather events. Bridging the gap requires better understanding of the primary drivers of adaptation planning and the emerging adaptation options across a range of scales. This dissertation explores the relationships between primary factors driving adaptation planning initiatives for specific cases in North America (United States and Canada) and the selection of adaptation options related to risk of flooding events across scales in their urban contexts.

The guiding question formulated for this study was: What are the relationships between primary factors driving climate adaptation planning initiatives and the selection of adaptation response options related to risk of urban flooding events across spatial scales? The supporting questions include: (1) what are the primary factors driving climate adaptation planning initiatives related to risk of urban flooding events, and (2) what are the emerging adaptation response options related to risk of urban flooding events across a range of cases?

A modified Drivers-Pressures-States-Impacts-Responses (DPSIR) framework developed by Rounsevell, Dawson, and Harrison (2010) was used to organize the information from adaptation planning case studies and explore relationships between primary factors driving adaptation planning and the emerging adaptation response options from a social-ecological systems (SES) perspective of urban environments (Rounsevell et al. 2010). For this dissertation, the coupled framework was significant in structuring, visualizing, and organizing relevant relational data (Dawson et al. 2010) from the selected individual adaptation planning case studies across a range of scales.

In the coupled DPSIR-SES framework, drivers (either internal or external) reflect the interplay between socio-economic activities and environmental processes, and how they are manifest in pressures that generate change (impact) to the state of intertwined social-ecological systems (Dawson et al, 2010; Kelble et al. 2013). Impacts are seen as positive or negative effects in the state of SES (Rounsevell, 2010). Responses emerge as a result of pressures, states and impacts, but responses rarely directly affect drivers (Keble et al. 2013).

The systematic review approach[6] provided a means to identify, examine, and synthesize both qualitative and quantitative data derived from individual adaptation planning case studies to generate objective and generalizable findings that address the research questions (Garg et al. 2008; Mantyka-Pringle et al. 2012; Stewart et al. 2013).

1.3 Hypothesis

Hypothesis: There is evidence of association between primary factors driving adaptation planning initiatives and the selection of adaptation options.

The study hypothesis was based on the modified DPSIR-SES model framework (Rounsevell et al. 2010) that suggest there are possibilities of deriving primary drivers of adaptation planning in the context of urban SES from the interactions of pressures-states-impacts (PSI) components of the framework. However, the pressure-state and state-impact relationships

[6] A systematic review involves: 1) an explicit keyword and specialist search of adaptation planning initiatives from available project databases and documents; 2) clear inclusion/exclusion criteria for case studies identified; 3) extraction of case study information (e.g. geographic location, driving factors, emerging response options among other variables) to create a dataset stored in MS Excel worksheet; and 4) coding and analysis of selected cases (Brooks et al. 2013; Ford et al. 2011; Munroe et al. 2012).

are much more complex and dynamic than a simple transformation (Rounsevell et al. 2010). Response options are feedback loops that reflect different response strategies that aim at minimizing impacts (or maximize positive impacts or benefits) by acting on the interactions between the pressures-states-impacts variables (Rounsevell et al. 2010). Thus, the selection of adaptation response options seems to be dependent on the fit between the impacts or benefits that urban communities experience in relation to the interacting pressures-states-impact variables.

As planners, designers, and policy-makers identify and map the interactions between the pressures-states-impacts variables, a clear understanding of the primary driving factors associated with adaptation planning initiatives can be developed and subsequently used to select, implement, manage, and evaluate adaptation response options across a range of scales in the urban context.

1.4 Significance of study

Evidence exists that a growing number of cities around the globe have initiated adaptation planning using a wide range of databases, models, and visualization tools in complex design and decision-making environments (Carmin et al. 2012b). However, there exists barriers to implementation of adaptation planning outcomes, resulting in a widely recognized 'planning-implementation gap' across a range of scales and regions (Bierbaum et al. 2012).

This study is timely with the great need for bridging the gap between adaptation planning and implementation of adaptation options (also referred to as a 'planning-implementation gap') that exists in the face of changing climate (e.g. sea-level rise) and extreme events (e.g. flooding) across a range of regions and scales in the urban context (Berrang-Ford, 2011; Bierbaum et al. 2012; Ford et al. 2011; Fussel 2009). The results of this study are significant in narrowing the 'planning-implementation gap' in three main ways.

First, understanding the relationships between primary drivers of adaptation planning initiatives and the selection of emerging adaptation options can guide the design and/or scaling-up of interventions for better climate adaptation (for example the restoration of vital natural ecosystems and the creation of integrated and resilient green infrastructure networks), improved institutional frameworks (namely better land use regulations and policy), and increased social learning (Bierbaum et al. 2012; Plummer and Armitage, 2010). Improving the understanding of the range of factors that influence adaptation response options can encourage organizations to develop strategies appropriate to their particular circumstances when taking on the challenge of planning for a changing climate and extreme events.

Second, the implementation and management of robust adaptation actions that promote urban resilience in the face of changing climate and extreme events require an understanding of (and learning from) the interactions between primary drivers of adaptation planning initiatives and the emerging adaptation response options across spatial scales and the feedbacks generated by the adaptation actions (Gagnon-Lebrun and Agrawala, 2011; Rounsevell et al. 2010).

Third, bridging the divide between planning and implementation/management of adaptation actions forms the basis for evaluation of planning outcomes to reduce uncertainty of targeted adaptation responses across regions and scales. For instance, the costs and benefits of specific adaptation planning initiatives can only be analyzed if the selected options are prioritized and effectively implemented as targeted actions.

1.5 Structure of the dissertation

This introductory chapter is followed by Chapter 2 which describes the theoretical and conceptual frameworks guiding this study by reviewing theories and concepts of social-ecological systems and resilience in the context of urban adaptation planning. This chapter includes review of related literature on climate change and extreme events, status of adaptation planning initiatives, planning support systems (PSS) and urban adaptation planning across scales, drivers of adaptation planning initiatives, the emerging adaptation response options and barriers to implementation adaptation planning actions across the globe—with a particular focus on North America.

Chapter 3 describes the research design and methodology for systematic review of adaptation planning cases across the North America and includes:- (a) an explicit keyword and specialist search of adaptation planning initiatives from available project databases and documents; (b) clear inclusion/exclusion criteria for case studies identified; (c) extraction of relevant case study information to create a dataset stored in MS Excel worksheet; and (d) coding and analysis of emerging information related to the selected plans and planning initiatives.

Chapter 4 presents the main results from the synthesis of data related to the objectives and primary question as well as the hypothesis of the study—seeking to better understand the association between primary factors driving climate adaptation planning initiatives and the selection of climate adaptation options. This chapter highlights the search strategy results, the characteristics of included studies, and the significant relationships between primary factors driving urban adaptation initiatives and the selection of adaptation options related to risk of urban flooding events.

Chapter 5 presents a discussion of findings and the advances made through this study in the understanding of the relationships between primary factors driving urban adaptation initiatives and the selection of adaptation options related to risk of urban flooding events, and concludes the dissertation with a summary discussion of key lessons, and further research directions.

Chapter 2 - Literature review

Urban adaptation has gained increasing recognition in recent years, due to the realization of its potential value to reduce the vulnerability of urban systems (natural systems, built environments, and human populations) and improve resilience of urban communities and environment to existing and future changing climate risks (e.g. sea-level rise) and related extreme events (e.g. drought and flooding) across a range of scales (Bierbaum et al. 2012; Preston, 2013). Recent observed trends in the frequency and magnitude of extreme events such as urban flooding and their perceived impacts pose great challenges for planning, design, and policy decision making across all regions (see e.g. Bierbaum et al. 2012; Carmin et al. 2012b).

A global survey by Carmin et al. (2012b) conducted between April and May, 2011 show that 74 percent of U.S. cities perceived changes in the climate, including increased storm intensity (31 percent), higher temperatures (30 percent) and more precipitation (28 percent). The cities surveyed identified primary challenges as follows: - increased stormwater runoff (72 percent), changes in energy demand (42 percent), loss of natural systems (39 percent), and coastal erosion (36 percent) (Carmin et al. 2012b). Other challenges that ranked closely behind were loss of economic revenue, drought, and solid waste management (Carmin et al. 2012b). Recent examples of climate variability and extreme events that have impacted urban built infrastructure, socio-economic and institutional frameworks and public health (Bierbaum et al. 2012) particularly in North America include hurricanes Katrina and Rita; Superstorm Sandy, and numerous typhoons in the Pacific.

In their survey, Carmin et al. (2012b) provided deeper insight into: (1) the status of adaptation planning globally, (2) the approaches that cities around the world are taking, and 3) the challenges cities are encountering as they seek to prepare for a changing climate. The survey shows that a wide range of cities are thinking about how they can be prepared for future extreme events.

Survey responses from 298 U.S. local governments indicated that 59 percent are engaged in some form of adaptation process (ranging from assessments to planning to implementation) (Carmin et al. 2012b). There is evidence that 48 percent of U.S. cities were in the preliminary planning and discussion phases – including gathering information, exploring adaptation options and/or holding informal consultations. The remaining 52 percent were either in the risk and vulnerability assessment phase (13 percent) or involved in plan development and implementation phases (39 percent) (Carmin et al. 2012b). The survey concludes that a considerable number of the responding cities are taking action to adapt to climate change via planning or through the process of implementation.

2.1 Theoretical and conceptual framework

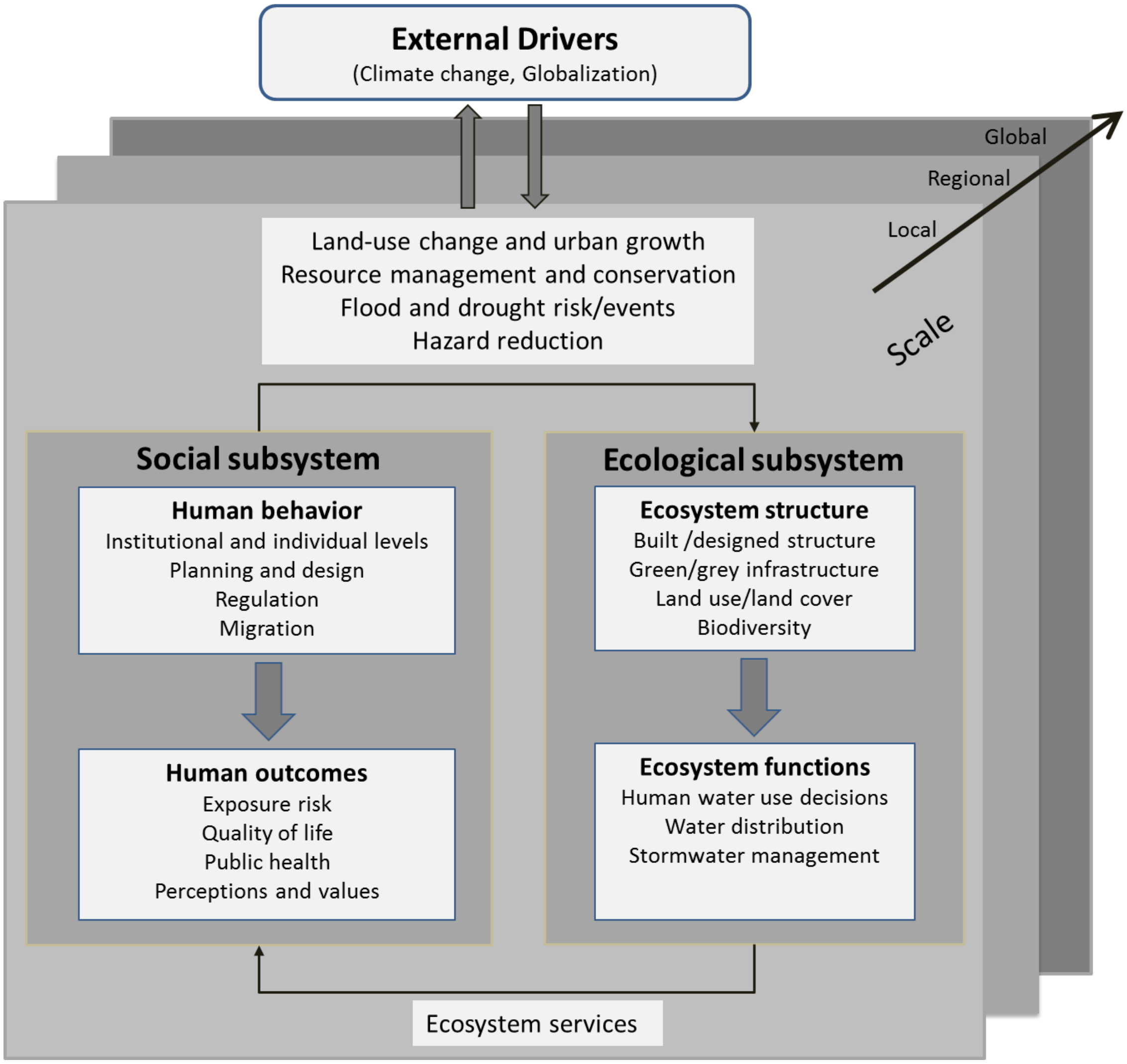
Urban climate adaptation processes consist of planning initiatives, actions, and adjustments (both incremental and transformational) that aim to reduce vulnerability while increasing the resilience of natural systems, the built environment, and human populations to actual and anticipated change (Carmin et al. 2012; IPCC, 2007; Kates et al. 2012).

This theory and concepts section (1) reviews the linkages between urban vulnerability, adaptive capacity, and resilience in the context of social-ecological systems, (2) introduces the modified Drivers-Pressures-States-Impacts-Responses and Social-Ecological Systems (DPSIR-SES) conceptual framework, and (3) explores the issue of scale.

2.1.1 Urban vulnerability, adaptive capacity, and resilience

Vulnerability, adaptive capacity and resilience are important concepts for understanding adaptation in the context of urban social-ecological systems (Grimm et al. 2012; Smit and Wandel, 2006). Urban social-ecological systems (SES) are characterized by interactions and feedbacks between external drivers, social (human), and ecological (natural) subsystems across multiple scales (Bai et al. 2010; Damm, 2010; Grimm et al. 2012). From a climate change perspective urban social-ecological systems (Figure 2.1) are mainly composed of (1) external drivers (e.g. changing climate); (2) press and pulse events (e.g. flooding risk and drought); (3) urban social subsystems comprised of human actions (including planning, design, and regulation) and outcomes (e.g. quality of life and public health); (4) urban ecological subsystems that include urban ecosystem infrastructure (e.g. built and designed structures, and green to grey infrastructure), and ecosystem functions ((climate regulation via sequestration of carbon dioxide); and (5) ecosystem services (such as water supply, stormwater management, and tempering of urban heat loads), all functioning across spatial (local, regional, and global) and temporal scales (Grimm et al. 2012).

Figure 2.1: Elements of urban social-ecological systems (SES)



Source: Modified from Grimm et al. 2013.

Urban social-ecological systems are unique in how they evolve as a result of myriad interactions between diverse actors (e.g. individuals, community, and governments), their choices and actions, and the emerging challenges of changing climate (such as sea-level rise for coastal cities) and flooding risks due to increased intensities of storm events (Alberti et al. 2003).

The choices and actions of actors have the potential to influence urban growth and development patterns (e.g. through land use and infrastructure density) and affect ecosystem processes (through land use change, resource consumption, and generation of emissions and waste) with potential impacts on ecosystem services, public health, and quality of life (Alberti et al. 2003). Thus, urban social-ecological systems constantly experience change and adaptation processes related to utilization, management, policy, ecological, and external influences within and across a range of scales (Folke, 2006).

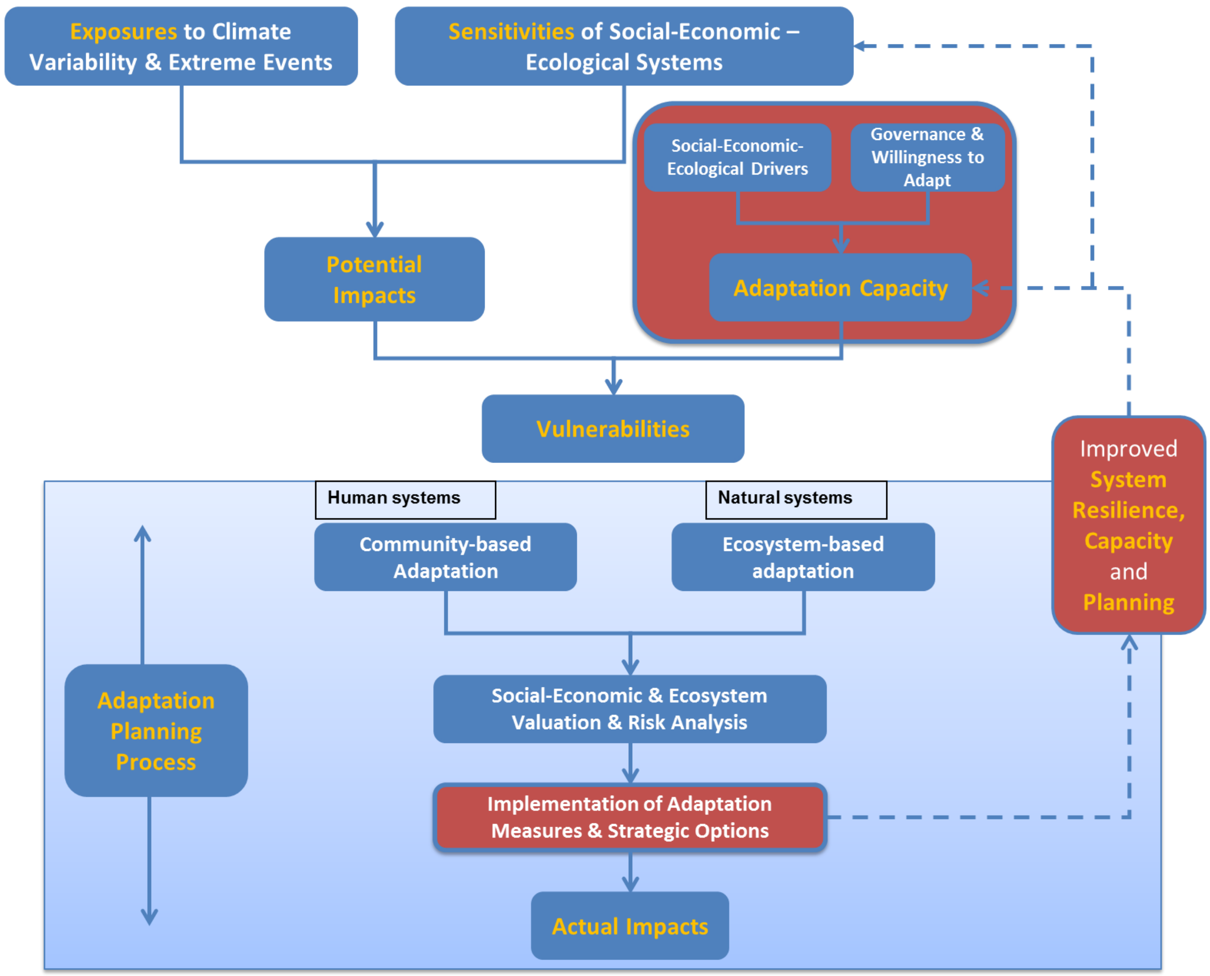
A number of adaptation studies have employed the generic framework shown in Figure 2.2 to understand the linkages between vulnerability, adaptive capacity and resilience of cities as social-ecological systems to address factors that interact to foster or impede climate adaptation processes across spatial and temporal scales. Studies emphasizing the need to create more resilient, adaptive cities across a range of scales are many, and include those by Adger et al. (2005), Smit and Wandel (2006), Lankao and Tribbia (2009), and Wilbanks (2009).

While urban vulnerability is the susceptibility of a city or region to significant climate change impacts that cannot be adequately addressed under present circumstances, adaptive capacity in the urban context is the ability or potential of the urban social-ecological systems to respond successfully to change, in order to reduce adverse impacts and take advantages of new opportunities (IPCC, 2007; Kates et al. 2012).

Vulnerability is a function of adaptive capacity and susceptibility to serious impacts and is directly connected to the sensitivity of social-economic-ecological systems to climate variability and extreme events (Bulkeley and Tuts, 2013). It is widely accepted that adaptive capacity is a social construct driven by factors operating at many different scales and highly varied within and between urban settings (Bulkeley and Tuts, 2013; Smit and Wandel, 2006). Physical constraints are important, but in most cases it is the social processes that increase or decrease adaptive capacity (Bulkeley and Tuts, 2013). The social drivers of adaptive capacity are varied but may include broad structures such as economic and political processes, as well as local structures such as access to information and knowledge for effective decision making and the structure of social networks and relationships within a community (Damm, 2010).

The resilience of urban social-ecological systems depends on the capacity of ecosystems to generate ecosystem services and the functional groups of species that provide these services, in combination with governance networks, social dynamics and the built environment (Damm, 2010; Folke, 2006).

Figure 2.2: Linkages between urban vulnerability, adaptive capacity, and resilience



Source: Modified from Lankao and Tribbia, 2009.

From this vantage point urban resilience refers not only to the amount of disturbances (change or variability) an urban social-ecological system can withstand before shifting to alternative states, but also the self-organizing capacity to retain the same structure and ways of functioning (Folke, 2006). Self-organization mechanisms allow urban social-ecological systems to absorb internal and external disturbances up to a level where thresholds are exceeded, then shift to alternative states – which may or may not result in undesirable outcomes and reduced functions (Adger et al. 2005; Folke, 2006; Liao, 2012).

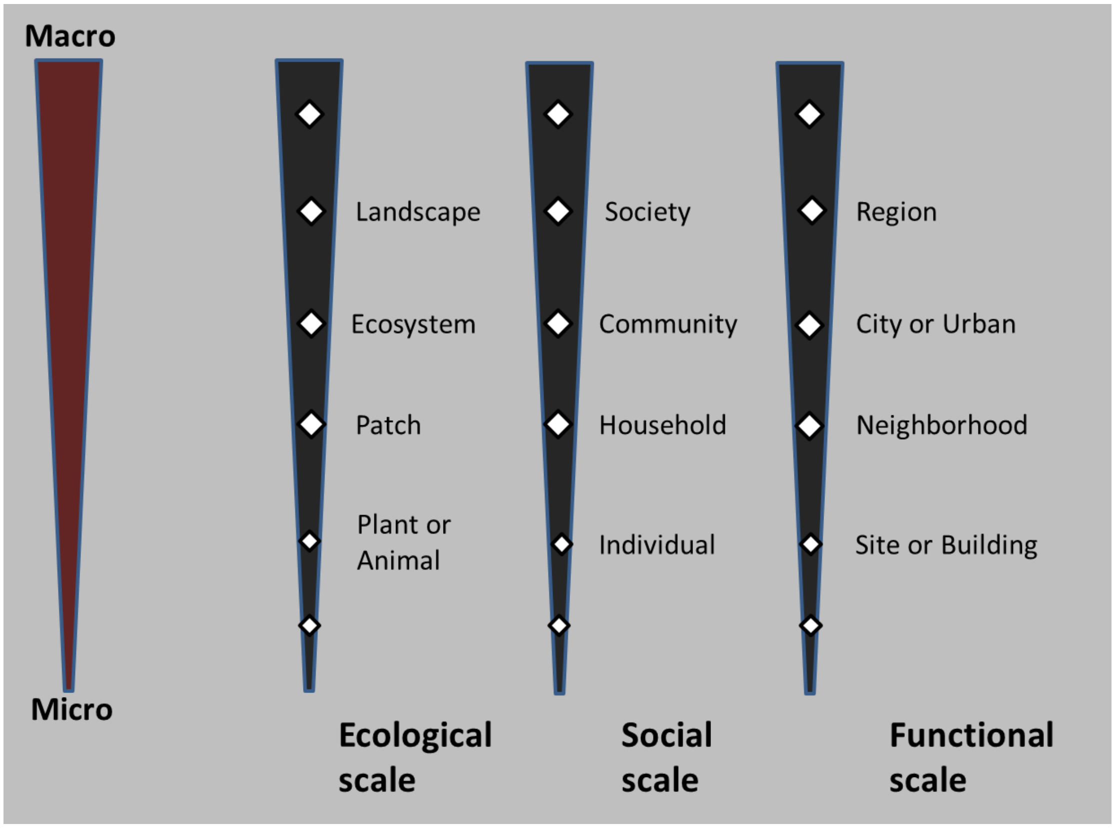
Urban adaptation can be seen as related to a system's level of resilience, which involves reflecting on and responding to current trends and projected changes to either reduce vulnerability and impacts of changing climate and extreme events, or harness new opportunities arising at interlinking scales (Folke, 2006). Urban adaptation emerges as a continuous heterogeneous process that involves planning initiatives, choices of options, and implementation of actions within and across spatial scales (Adger et al. 2005: Bierbaum et al. 2012).

2.1.2 Issues of scale and complexity

Urban adaptation planning for changing climate (e.g. sea-level rise) and extreme events (namely flooding and drought) involve social and decision processes that occur within and across space and time (Adger et al. 2005; Bierbaum et al. 2012; Poyar and Beller-Simms, 2010). Issues of scale (in space and time) and complexity of urban social-ecological systems have well acknowledged implications in the design of adaptation planning initiatives, development, assessment, and selection of adaptation options, and implementation of adaptation actions (Adger et al. 2005; Bierbaum et al. 2012; Wilbanks, 2009). Recognizing that various studies (see Cash et al. 2006; Gibson et al. 2000; Kok and Veldkamp, 2011) have conceptualized scale to include spatial, temporal, and other quantitative or analytical dimensions, this section only provides in-depth discussion on the spatial dimensions of scale, its levels (or units of analysis), and interactions.

Following Cash et al. (2006), "spatial scale" connotes the different functional dimensions of space, used to observe or measure and characterize or study phenomena, social patterns, and ecological processes. Figure 2.3 illustrates the ecological, social, and functional spatial scales and their respective levels of analysis that may be of significance in the current study (Damm, 2010). It emerges that the ecological and social spatial scales explain phenomena that exist in the social-ecological systems from the perspective of functional spatial scales that extends from site specific scale to regional scale and beyond (Damm, 2010). The functional spatial scale was identified to be of great importance for the assessment of plans that support urban adaptation to changing climate and related extreme events.

Figure 2.3: Ecological, social, and functional spatial scales in adaptation planning

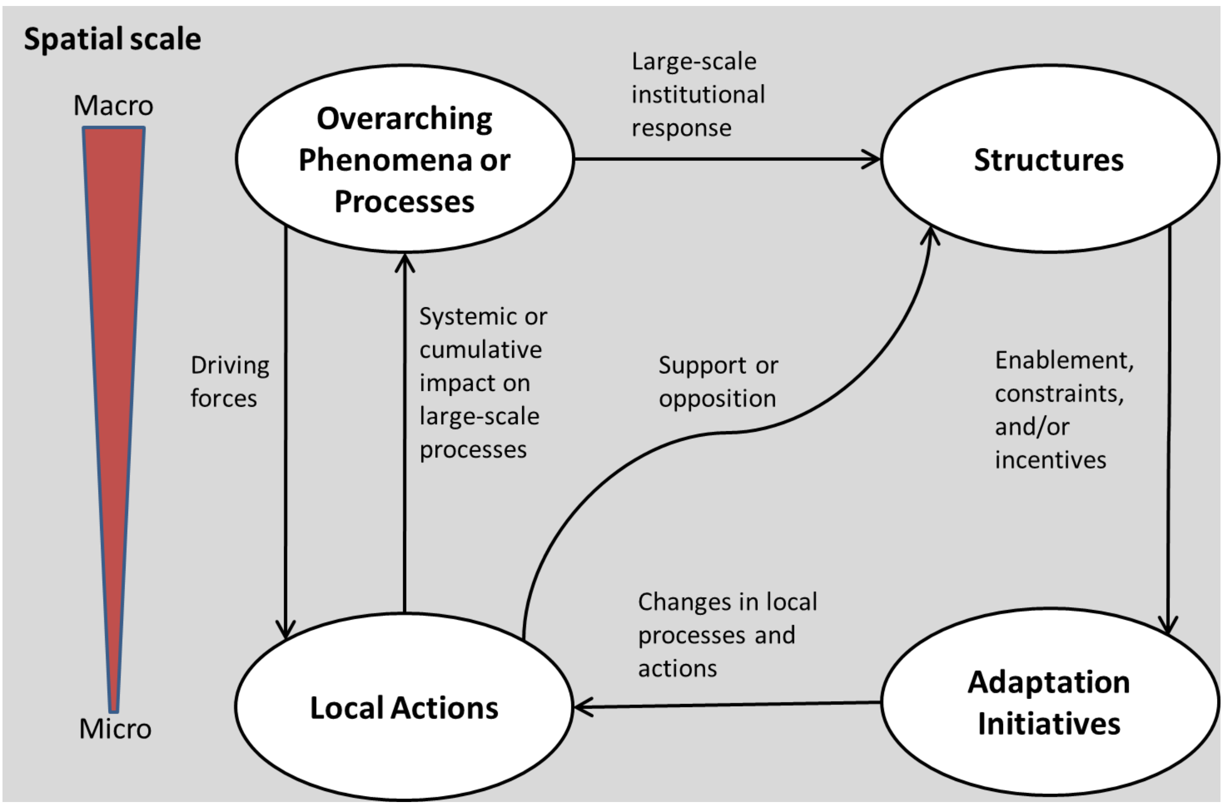


Source: Adapted from Damm, 2010

In the urban context, issues of complexity emerge from the dynamic interactions and linkages between community social patterns and ecosystem service processes within and across spatial scales (Cash et al. 2006; Damm, 2010). The scale dependent characteristics of urban social-ecological systems may emphasize the diversity of the factors motivating adaptation planning and affecting the ability to adapt—based not only on phenomena and geo-political context, but also on the social and ecological processes (Brooks, 2003; Damm, 2010; Wilbanks, 2007). Issues of scale may arise from the perceptions of risk, design of adaptation planning initiatives, and mismatches between the ecological and social scales with regard to prioritization of adaptation options, decisions, and implementation of actions with transboundary effects (see Adger et al. 2005; Cash and Moser, 2000; Folke et al. 2007; Gibson et al. 2000).

Figure 2.4 (adapted from Wilbanks, 2009) shows significant cross-scale interactions in urban social-ecological systems. For instance, overarching phenomena and processes at macro scale (such as urban policies and market signals) interact to influence local actions that conversely accumulate to impact or "drive" macro scale processes and structures (Wilbanks, 2009). In the same vein, "institutional responses on larger scales, shaped by democratic support or opposition from smaller scales, lead to large-scale structures that enable, (or constrain)" adaptation initiatives at the local scale (Damm, 2010: 30).

Figure 2.4: Cross-scale interactions in the context of urban social-ecological systems



Source: Adapted from Wilbanks, 2009

The spatial scale becomes a key consideration in adaptation planning since not all scales are suitable for design, development, and implementation adaptation options and actions (Johnson and Breil, 2012). For instance, individual or household responses to changing climate and extreme flooding events are less likely to require planning interventions given limitations of resources for effective adaptation planning process (Adger et al. 2005). Most adaptation planning initiatives are undertaken from community-scale to regional or national scales requiring more resources, investment and involvement of many participants (Johnson and Breil, 2012).

According to Adger et al. (2005) spatial scale issues have significant implications on the successes or failures in the implementation of adaptation actions, while also determining the relevance of different factors influencing vulnerability, adaptive capacity and resilience. Omunga and Kim (2011) found that scale dependencies significantly influence the implementation of appropriate planning support approaches, models and tools for the design and development of adaptation options in environmental and land use-transportation planning practices.

Adger et al. (2005) examined multiple case studies and revealed that driving factors motivating adaptation planning initiatives and the emerging adaptation response options may exhibit multiple dynamic interactions with feedback loops across spatial scales. Other recent studies (e.g. Gagnon-Lebrun and Agrawala, 2011) have also revealed that the implementation of robust adaptation actions that promote urban resilience in the face of changing climate and extreme events require an understanding of (and learning from) the interactions and feedbacks between drivers of adaptation planning and the selection of adaptation response options across spatial scales.

It emerges that the issue of spatial scale is very important in understanding and assessing adaptation planning initiatives, particularly the question posed by this dissertation (Adger et al. 2005; Carmin et al. 2009; Wilbanks, 2009). The urban (city) scale was selected as the spatial unit of analysis in this research for two primary reasons: 1) a sufficient number of urban adaptation planning case studies were available from climate adaptation databases, 2) the objective to explore the relationships between what is driving cities to engage in adaptation planning initiatives and the emerging adaptation response options with regard to changing climate and the risks of extreme flood events can be provided best at city level (Bierbaum et al. 2012; Carmin et al. 2012b; Johnson and Breil, 2012; Da Silva et al. 2012). Drawing inspiration from Rounsevell et al. (2010), Brooks et al. (2013), and other authors noted above, the urban spatial scale of analysis influenced the conceptual framework as well as methodological approach of the present study.

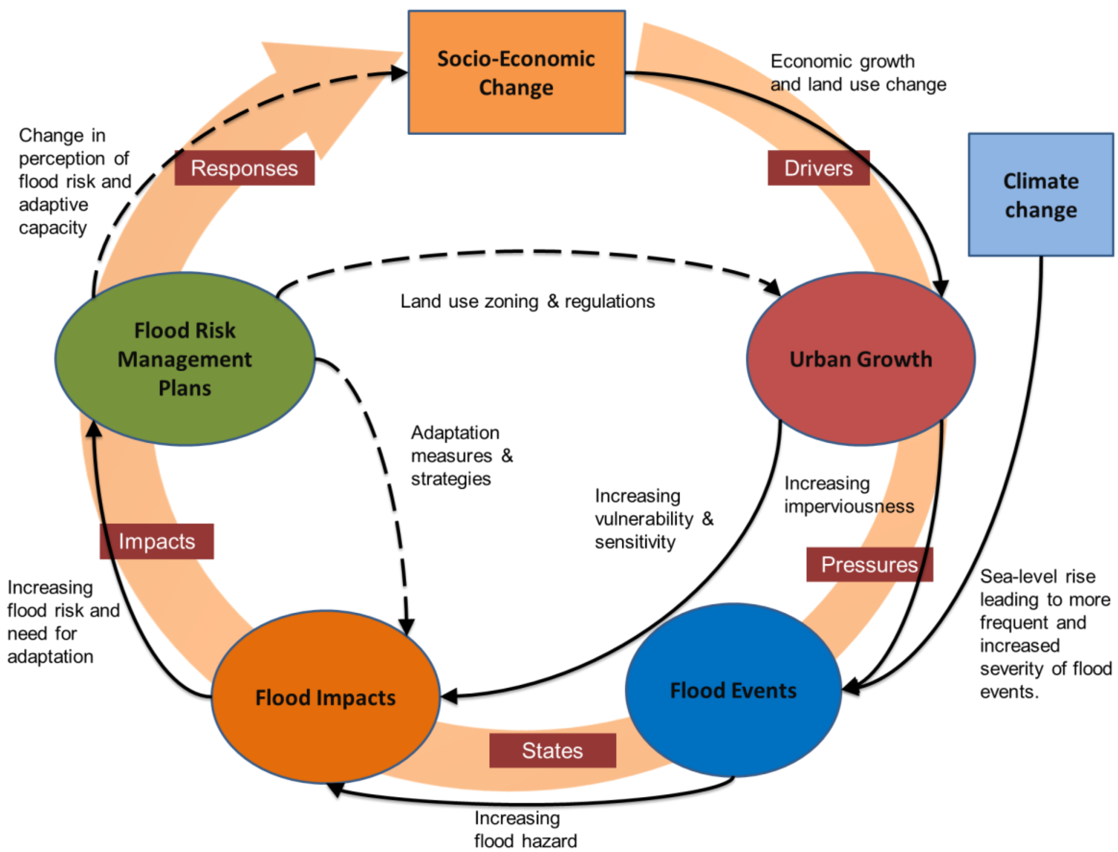
2.1.3 The DPSIR-SES conceptual framework

The Drivers-Pressures-States-Impacts-Responses (DPSIR) is one of the notable frameworks devised in the early 1990s aimed at structuring and organizing information on the relationships between human activities and the ecosystem services, across a range of scales from local to global (Kristensen, 2004; Sekovski et al. 2012). Since then, the framework has rapidly evolved as a systematic interdisciplinary approach and is now widely utilized for understanding causes, consequences and responses in global change assessments (e.g. Millennium Ecosystem Assessment), ecosystems and human-environment interactions research, sustainability and quality of life studies (Dawson and Rounsevell, 2008; Kristensen, 2004; Rounsevell et al. 2010; Sekovski et al. 2012).

Specifically, the utility of the DPSIR framework has been realized in exploring interactions and feedbacks between social-economic drivers, environmental pressures, state of change in environment and societal responses to the changes (Dawson and Rounsevell, 2008; Kurzbach et al. 2013; Rounsevell et al. 2010; Sekovski et al. 2012; Song and Frostell, 2012). Rapidly emerging areas of application include assessing strategies for forest management and evaluating sustainability of coastal areas, integrated catchment-coastal zone management and urbanization, urban public health, and other water-related issues (Maxim and Spangenberg, 2006; Tscherning et al. 2012).

Figure 2.5 provides a simple representation of the DPSIR framework from the management perspective of flood risk resulting from future urban growth and climate change (Kurzbach et al. 2013). The DPSIR framework in Figure 2.5 has five interacting components as: (1) **Drivers** that are a reflection of past and present conditions or future scenarios and projections of socio-economic change related to economy, demography, technology and culture that may interact to drive the demand and supply of urban land, competition for space, and spatial planning, consequently producing different pressures (e.g. land use/cover changes) to urban social-ecological systems (SES); (2) **Pressures** (e.g. land-use/cover change) which combined with scenarios of changing climate and extreme events may exert change on the state of urban systems in the form of increasing imperviousness and stormwater runoff, flood risk and vulnerability to extreme flooding events, and the delivery of ecosystem services; (3) **States** describe the quality and sensitivity of the whole social-ecological system (including supporting systems, actors and ecosystem services) to current and future trends of pressures and related variables; (4) **Impacts** are the result of changes in state variables associated with SES that may increase perceived risk and the social, environmental, and economic effects of flooding events to provoke the need for adaptation planning, investment, and policy responses across urban scales; (5) **Responses** generate a feedback (at times simultaneous) towards all other components of the framework (Dawson and Rounsevell, 2008; Kristensen, 2004; Kurzburch et al. 2013; Rounsevell et al. 2010; Sekovski et al. 2012).

Figure 2.5: Drivers-Pressures-States-Impacts-Responses (DPSIR) model framework applied to climate change and urban flood risk management



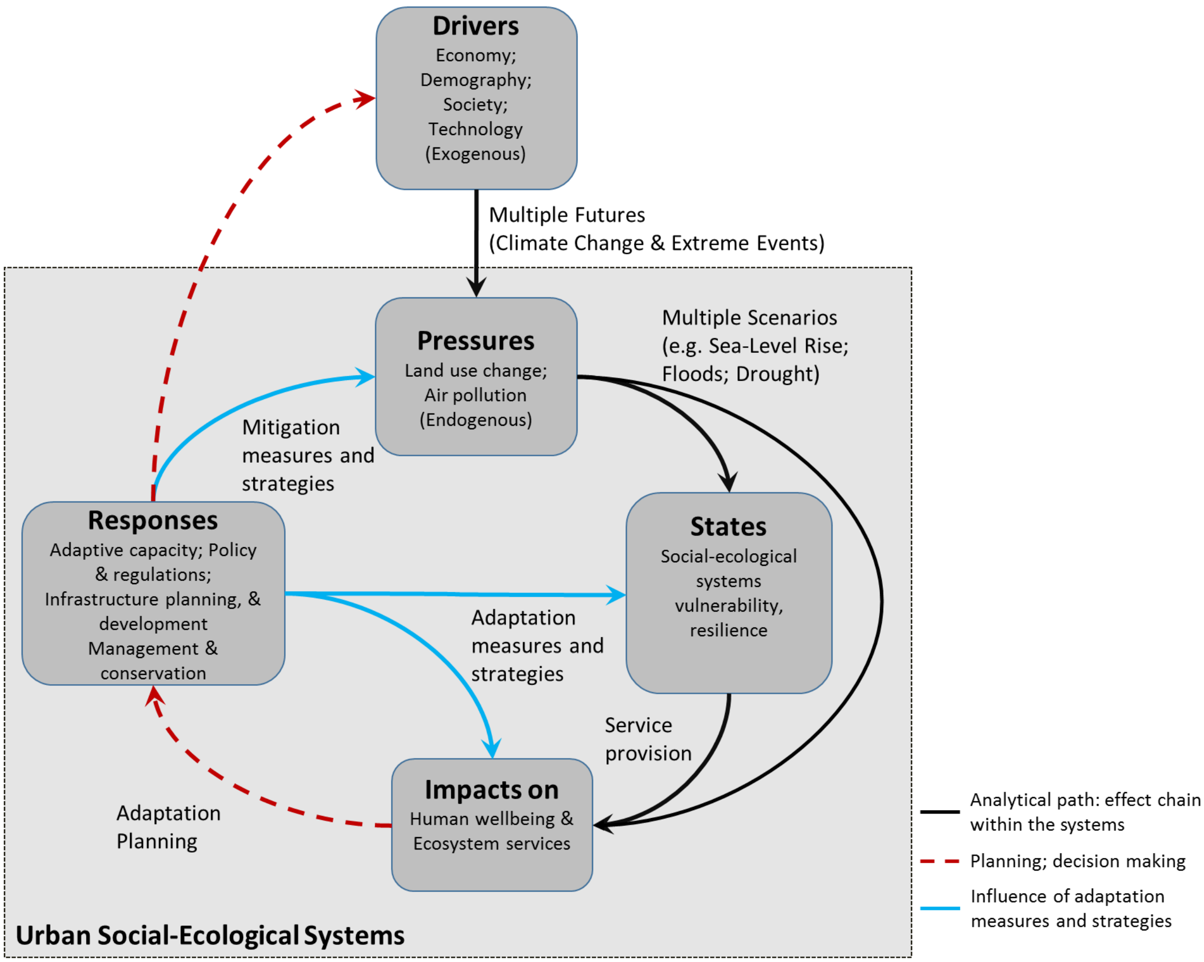
Source: Adapted from Kurzbach et al. 2013.

However, the DPSIR framework displays inconsistencies in its application to environmental problems, namely the use of terminology such as “drivers” within particular fields of research (Kristensen, 2004; Rounsevell et al. 2010). The DPSIR model has also been criticized for its simplistic ‘one-size-fits-all’ approach to human-environment phenomena, unclear cause-effect relationships, and failure to capture dynamics of complex adaptive interrelationships (especially in urban systems) that are crucial in planning and decision making (Kristensen, 2004; Song and Frostell, 2012). The various components can be interpreted differently depending on context and focal question of any analysis, especially in complex urban social-ecological systems (Rounsevell et al. 2010).

The modified Driver-Pressure-State-Impact-Response and social-ecological systems (DPSIR-SES) framework (Figure 2.6) adapted from the framework published by Rounsevell et al. (2010) provided a robust conceptual framework for the present research. The framework provided a useful platform for structuring and organizing information needed to explore the relationships between primary factors driving adaptation planning initiatives and the emerging adaptation options related to risk of flooding events across scales in the urban context (Rounsevell et al. 2010). The significance of the modified DPSIR-SES framework in this dissertation is improved understanding of cross-scale dynamics and the interactions between pressures, states, and impacts (the pressure-state change-impact (P-S-I) linkage) that influence engagement in adaptation planning initiatives to generate specific adaptation response options across urban spatial scales (Kelble et al. 2013; Rounsevell et al. 2010; Weng, 2011). Also from the systems perspective, non-linear processes and interaction models can be developed within the DPSIR-SES framework to facilitate policy and investment decision-making in complex urban environments (Rounsevell et al. 2010).

Based on the modified DPSIR-SES framework, it emerges that there are possibilities of deriving primary drivers of urban adaptation planning from the interactions of pressures-states-impacts (P-S-I) components (Iannucci et al. 2011). However, it should be noted that the pressures-states and states-impacts relationships are much more complex and dynamic than a simple transformation (Rounsevell et al. 2010). “The states may change in response to the pressures in dynamic ways as characterized by concepts such as urban resilience and robustness” to reach certain thresholds that have a negative (or positive) impacts on human health and wellbeing, the economy, specific ecosystems, and other environmental resources (Rounsevell et al. 2010:2829). Response options are feedback loops that reflect different response strategies that aim at minimizing impacts (or maximizing positive impacts or benefits) by acting on pressures-states-impacts interaction variables (Rounsevell et al. 2010).

Figure 2.6: The modified DPSIR-SES conceptual framework



Source: Modified from Rounsevell et al. 2010.

The modifications were made in the conceptual framework (Figure 2.6) in order to adapt the framework to the theoretical underpinnings of adaptation planning and urban resilience (Adger et al. 2005; Folke, 2006; Grimm et al. 2012) and the demands of present research. The modifications relate to the concepts discussed in the previous and the following sections.

2.2 Planning support systems and adaptation planning across scales

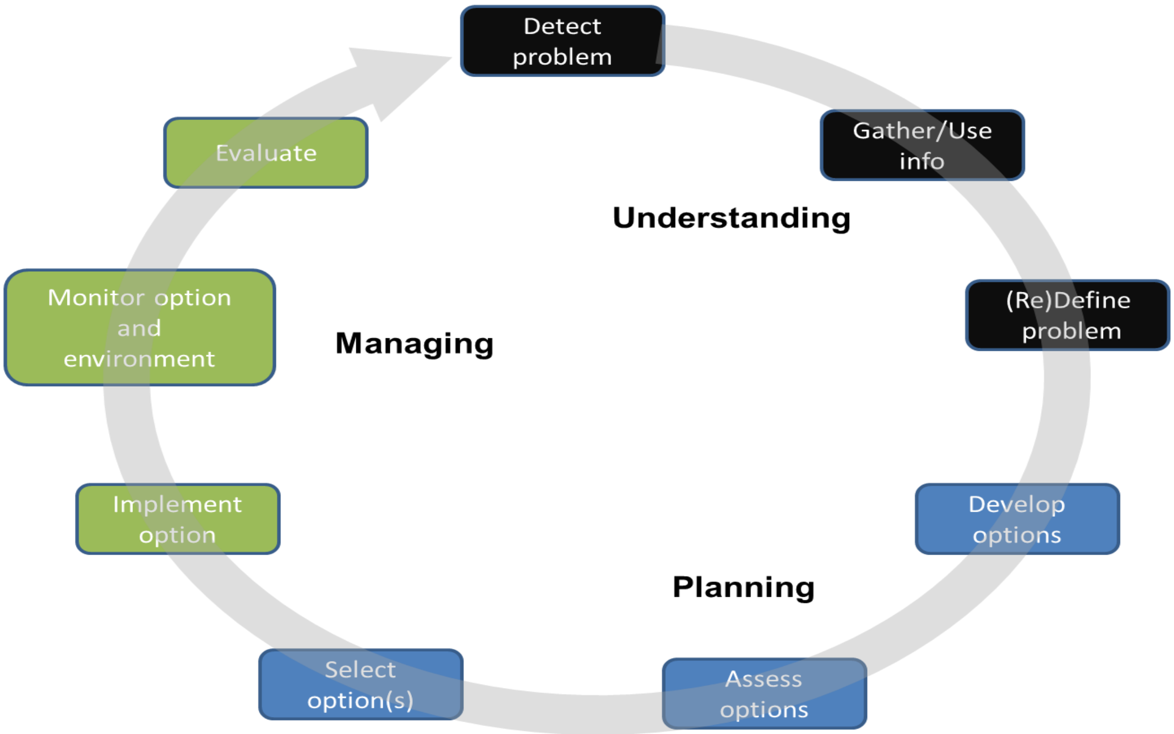
Urban adaptation planning has been increasingly acknowledged to offer new possibilities for responding to the current and potential effects of changing climate (e.g. sea-level rise) and extreme events (e.g. drought and flooding) in regards to land use, built infrastructure, water quality, and public health across different scales (Berrang-Ford et al. 2010; Bierbaum et al. 2012; Carmin et al. 2012b; Ford et al. 2011; Hallegate and Corfee-Morlot, 2011).

Evidence exists that a growing number of cities around the globe have initiated adaptation planning using a wide range of databases, models, and visualization tools in complex design and decision-making environments (Carmin et al. 2012b). In addition, recent years have witnessed many types of planning support systems (PSS), designed to enhance various planning tasks (e.g. data collection, analysis, collective decision-making, etc.) and eventually to realize a more efficient, robust and collaborative planning process. (Klosterman and Pettit, 2005; Batty, 2008).

According to Geertman and Stillwell (2004), PSS inventory includes a broad range of tools that support visualization, communication, and interaction as well as problem solving (i.e., modeling, analysis, and simulations). Systematic integration of data, models, and visualization components has also been achieved and integrated support systems are now available for planning practitioners in the field (Geertman and Stillwell, 2009).

Emerging climate adaptation research effectively combined with advances in planning support systems (PSS) – integrating databases, models and visualization tools – offers new frameworks to support each of the phases and stages of the adaptation process depicted in Figure 2.7, and contribute significantly to understanding, planning, anticipating and effectively responding to the impacts of changing climate and related extreme events (Batty, 2008; Chakraborty et al. 2012; Geertman and Stillwell 2009; Klosterman and Pettit, 2005; Moser and Ekstrom, 2010; Vonk and Geertman, 2008).

Figure 2.7: Moser and Ekstrom's phases and stages of the adaptation process



Source: Redrawn from Moser and Ekstrom, 2010:22027

In adaptation planning process, there are reported similarities in approaches (broadly categorized as community-based and ecosystem–based). These approaches are employed to develop, assess, and select options for response to current and future impacts of climate change and related extreme events across a range of scales (Bierbaum et al. 2012; Hunt and Watkiss, 2011; Moser and Ekstrom, 2010; Preston et al. 2013).

Cities may focus on impact-oriented ("top-down") and/or integrated capacity-focused ("bottom-up") adaptation planning approaches to explicitly identify, evaluate adaptation options, and generate effective, robust, and flexible adaptation measures and strategies (Adger et al. 2005; Bierbaum et al. 2012; McCarthy, 2012; Preston et al. 2013). Top-down approaches consider climate risks, vulnerabilities and impacts as the basis for adaptation planning while bottom-up approaches focus on participatory approaches, are place-based and scenario development forms the basis for projective evaluations of what the future may hold (Adger et al. 2005).

Although there are reported similarities in approaches to adaptation planning, cities are employing various qualitative and quantitative methodologies (such as case studies, scenario analyses, and sensitivity analyses) and tools (modeling, and visualization) to vulnerability or risk assessment, plan development and implementation of emerging adaptation actions at different spatial scales (Bierbaum et al. 2012; Hunt and Watkiss, 2011; Preston et al. 2013). The emerging modeling and enhanced visualization tools have been employed to: (1) promote understanding by making climate change and adaptation explicit to planners' and other engaged stakeholders'; (2) facilitate their dialogue between a range of stakeholders; (3) contribute to social learning; and eventually (4) support more informed decision-making throughout the various phases and stages of adaptation process (Batty, 2008; Burch et al. 2010; Sheppard et al. 2011).

2.3 Implementation of planning support systems

Given that the claimed potentials of planning support systems (PSS) can be realized only when they are employed in real world planning practices, increasing attention has been paid to the implementation of the support systems.[7] For instance, Vonk (2006) conducted a series of expert interviews and a web-based survey to see how various types of PSS have been received by the planning profession in the field. Vonk found that a majority of planners in the field have not fully utilized planning support systems in their daily work due to the lack of user's awareness, experience, and motivations to utilize many of the support systems (2006).

Te Brömmelstroet (2010) also conducted a survey of Dutch land use and transportation planning practitioners and received a considerable number of responses, saying that planning support systems are "implemented too late in the planning process," "too far from the political process," and/or "do not fit the … [target] planning process" (p.31-32). There is other evidence showing that in real applications, the full potentials of PSS are yet to be realized (see for example, Geertman and Stillwell, 2009).

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[7] PSS potentials for a broad range of planning practices have been discussed in many studies. For instance, recently, Te Brömmelstroet (2010:28) contended that PSS can help "1) to facilitate interaction among planners; 2) to contain structured and accessible information; 3) to facilitate social interaction, interpersonal communication and debate (in order to address common concerns); and 4) to support continuous and interactive process of constantly integrating new information (generated as analytical results) and thus redefining design issues." It is claimed that PSS is a promising tool that planners need to possess to deal with wicked planning challenges posed by increased complexity and uncertainty of urban systems (Brail 2008). For additional discussions, see Harris (1989); Harris and Batty (1993); Klosterman (2001); Brail (2005); Geertman (2006); Vonk et al. (2007); Geertman and Stillwell (2009).

Understanding the implementation issues becomes critical in PSS literature and some recent studies attempt to answer the question "why not implemented as much as expected, despite great potential usefulness?" Vonk et al. (2005) is a notable study, examining and discussing the PSS implementation issues. According to Vonk and colleagues, there are various human, organizational, institutional, and technical factors that can cause under-utilization of PSS in real world planning practice. These include the lack of trained human resources able to use complex PSS; lack of organizational infrastructure and readiness to adopt PSS; and institutional resistance to technological changes (Vonk et al. 2005).

In a follow-up study by Vonk and Geertman (2008), more careful consideration is given to the barriers to the PSS implementation on both supply-side and demand-side. On the supply-side, the following bottlenecks are found – "little insight … into the features that characterize a PSS…; little proof of the actual value of PSS…; technology-oriented rather than user-driven approach to PSS development…; [and] limited usage of PSS across national boundaries" (Vonk and Geertman 2008:158-159). On the demand-side, it is reported that "the main bottlenecks … [include] a lack of awareness concerning the existence and potential of PSS in planning practice, a lack of experience in using PSS and a general lack of intention to use PSS by the actors in the planning community" (p.159). The authors also find that PSS adoptions can often be hindered by supply-demand mismatches, including poor fitness of technology (Vonk and Geertman, 2008).

Pozoukidou (2006) also examines the critical barriers to active adoption of PSS. Here, twenty metropolitan planning agencies are asked to respond to a set of survey questionnaires after having a trial of a support system, called "TELUM.' According to the agencies' responses, external barriers include – "obstacles that are not directly related to the developer or the user, but are more general issues that affect the applicability of models in planning practice … [such as] lack of appropriate quantitative education" for planning professional (p.13). Such barriers are regarded as the most significant challenge for implementation. The second and third most challenging barriers are "lack of operational support from the developer or the provider of the software" and "the extensive data requirements" (Pozoukidou 2006:14).

Although the above studies indeed shed light on the PSS implementation barriers, there are adaptation-related environmental planning projects where PSS have been employed for their planning purposes (Omunga and Kim, 2011). For instance, The Ecosystem-Based Management

(EBM) Tools database compiled twenty-nine environmental planning projects (as of June 2011) where various kinds of PSS had been employed. The projects included planning works for environmentally sensitive and hazard-prone areas; planning efforts to create sustainable communities; community-based ecosystem management; and ecological impact assessments (Omunga and Kim, 2011). The Federal Highway Administration (FHWA) Planning Tools database provided a list of land use – transportation planning practices that utilized widely defined tools (including design guidelines and funding tools as well as support systems). Some of the projects with PSS have been documented; and the materials are useful resources for studying the PSS implementation in real planning practices.

In examining the EBM Tools database, Omunga and Kim (2011) found that two specific planning tasks – (1) *problem exploration and analysis,* and (2) *change exploration and analysis* – were the main targets of PSS applications.[8] For instance, in the Coastal Storms Initiative project in Brevard and Volusia Counties, Florida, the project group used NOAA's (National Oceanic and Atmospheric Administration) Risk and Vulnerability Assessment Tool (RVAT: http://www.csc.noaa.gov/rvat) to explore risk and vulnerabilities arising in the area due to the Florida coastal storms, and analyzed the coastal hazard and mitigation scenarios in an interactive manner ("Coastal Storms Initiatives," n.d.). In the case of a project, titled Watershed-based Analysis of Threats to Coral Reefs, the analytic tasks for their environmental planning have been supported by the N-SPECT: Nonpoint Source Pollution and Erosion Comparison Tool (www.csc.noaa.gov/nspect). More specifically, the PSS has been implemented "to derive estimates of runoff, erosion, and pollutant sources from across the landscape and examine the transport of sediment and pollutants" ("Costal Storms Initiatives," n.d.). Another example is the Solomon Islands project where SimCLIM (http://www.climsystems.com/simclim/), a climate change impact and adaptation software, has been applied (Simpson et al. 2009). This PSS is used to analyze significant changes in climate and associated problems including, "coastal hazards," such as hurricane-driven storm surges and "extreme high tides" that will likely arise due to future

[8] More than a half of the projects from the EBM Tools database adopted PSS for the analytic purposes. It also needs to be noted that most of the projects, where 1) *problem exploration and analysis* are conducted with supports of one or more PSS, utilized the tool(s) for 2) *change exploration and analysis* as well.

climate change and be exacerbated by increasing human settlement and/or degraded land conditions within certain coastal zones (Simpson et al. 2009, p.48).

It appears that this pattern is even stronger in the projects from the FWHA Planning Tools database that contain land use and transportation planning practices. Most applications were primarily utilized for both *problem exploration and analysis* and *change exploration and analysis*. For example, "Paint the Town," a customized version of the INDEX (www.crit.com/), has been used by the Mid-America Regional Council (MARC), in exploring land use and transportation problems and developing alternative future growth scenarios (MARC, 2008). The San Diego Association of Governments employs I-PLACE3S (http://places.energy.ca.gov/) for analytic purposes during the neighborhood planning process. I-PLACE3S helped planners explore neighborhood problems, generate various scenarios, and analyze potential changes in land uses while taking specified economic and regulatory constraints into account (DKS Associates et al. 2007).

In sum, the findings of Omunga and Kim (2011) demonstrated the utility of planning support tools for assisting with adaptation strategies in general and specifically helping the adaptation planning process such that the full potential of PSS are realized (see, for one example, Geertman and Stillwell, 2009).

2.4 Status of adaptation planning initiatives in North America

Adaptation planning effectively represents social and decision processes that facilitate implementation of interventions to reduce vulnerability and/or take advantage of potential opportunities associated with climate variability and change (Preston et al. 2010). A recent global survey conducted in 2011 by Carmin and colleagues (2012b) entitled, "Progress and Challenges in Urban Climate Adaptation Planning" attracted responses from 468 cities worldwide and provided deeper insight into: (1) the status of adaptation planning globally, (2) the approaches that cities around the world are taking, and (3) the challenges cities are encountering as they seek to prepare for a changing climate. Responses to this survey indicate that 68 percent of the responding cities of varying sizes across geopolitical scales are taking action to adapt to climate change and related extreme events via planning or implementation of selected strategies (Carmin et al. 2012b).

For instance, responses from 298 U.S. cities participating in the survey indicated that 59 percent were engaged in some form of adaptation planning initiative (Carmin et al. 2012b). According to the report 48 percent of the U.S. cities engaged in adaptation planning process (ranging from assessments to planning to implementation) were in preliminary planning and discussion phases (either gathering information, exploring adaptation options or holding informal consultations), while the remaining 52 percent were either in risk and vulnerability assessment phase (13 percent) or plan development and implementation phases (39 percent) (Carmin et al. 2012b). Survey responses from Canadian cities indicate that 92 percent are engaged in adaptation initiatives while the status analysis shows that 69 percent of the cities initiating adaptation planning were equally distributed between preparatory planning phase, initial planning phase, and risk or vulnerability assessment, 31 percent were in plan development/approval and implementation phases (see Carmin et al. 2012b).

Bierbaum et al. (2012) recently reviewed existing and planned climate adaptation initiatives by regional and local governments, nonprofit organizations, and private sector entities throughout the United States, including technical inputs to the 2013 United States National Climate Assessment (NCA), they noted that most adaptation actions were focused more on incremental change than wide-scale transformational shifts. The comprehensive review study conducted by Bierbaum et al. (2012) provided a number of examples of current climate adaptation initiatives and communities currently implementing prioritized options that include Grand Rapids, Michigan; Keene, New Hampshire; New York City, New York; Seattle (King County), Washington; and Chicago, Illinois. Table 2.1 (below) details a number of examples of urban adaptation initiatives to highlight the types of adaptation activities taking place in U.S. cities and states, and at regional levels (Bierbaum et al. 2012).

Studies in the Great Lakes Region (Barclay et al. 2013; Gregg et al. 2012) focus on how cities and people can adapt to climate change while remaining or becoming more economically, socially, or ecologically resilient. In their integrated assessment of four cities (Barclay et al. 2013) measure adaptive capacity and examine how each city government manages that adaptive capacity to achieve positive adaptive outcomes.

Table 2.1: Selected examples of U.S. City/State/Regional level adaptation initiatives related to climate change and flooding, stormwater management and/or sea level rise

City/State/Region	**Adaptation Initiative**
Satellite Beach, FL	Collaboration with the Indian River Lagoon National Estuary Program led to the incorporation of sea-level rise projections and policies into the city's comprehensive growth management plan (Gregg et al. 2011).
Portland, OR	The City of Portland, Oregon created a Climate Action Plan and updated the city code to require on-site stormwater management for new and re-development. The city offers a downspout disconnection program to promote on-site stormwater management (EPA, 2010b; www.portlandoregon.gov/bps/article/268612).
Lewes, DE	In partnership with Delaware Sea Grant, ICLEI-Local Governments for Sustainability, the University of Delaware, and state and regional partners, the City of Lewes undertook an intensive stakeholder process to integrate climate change into the city's updated hazard mitigation plan (www.ci.lewes.de.us/Hazard-Mitigation-Climate-Adaptation-Action-Plan/).
San Diego Bay, CA	Five municipalities partnered with the port, the airport, and more than 30 organizations with direct interests in the future of the Bay to develop the San Diego Bay Sea-level-rise Adaptation Strategy. The strategy identified key vulnerabilities for the Bay and adaptation actions that can be taken by individual agencies, as well as through regional collaboration (Solecki and Rosenzweig, 2012).
Chicago, IL	The City of Chicago has integrated climate adaptation into a citywide Climate Adaptation Plan. Since its release, a number of strategies have been implemented to help the city manage heat, protect forests, and enhance green design, such as their work on permeable surfaces and green roofs (www.chicagoclimateaction.org/pages/adaptation/11.php).
King County, WA	In Washington State, the King County Flood Control District reformed in 2007 to address increased impacts from flooding via activities such as maintaining and repairing levees and revetments, acquiring repetitive loss properties, and improving countywide flood warnings (Wolf, 2009; www.nerrs.noaa.gov/doc/pdf/training/strategies_king_county.pdf).
Keene, NH	The City of Keene, New Hampshire replaced culverts with larger ones that were designed to withstand projected increases in precipitation and population demand (www.ci.keene.nh.us/sites/default/files/CMPprint-final-1027-fullversion_2.pdf).
New York City, NY	Through a partnership with the Federal Emergency Management Agency (FEMA), the city is updating FEMA Flood Insurance Rate Maps based on more precise elevation data. The new maps will help stakeholders better understand their current and future flood risks, and allow the city to more effectively plan for climate change (City of New York, 2012). The city has also created a Green Infrastructure Plan and is committed to goals that include the construction of enough green infrastructure throughout the city to manage 10% of the runoff from impervious surfaces by 2030 (www.nyc.gov/html/dep/html/stormwater/nyc_green_infrastructure_plan.shtml).
Grand Rapids, MI	The City of Grand Rapids, Michigan released a Sustainability Plan that integrates future climate projections to ensure that the economic, environmental, and social strategies embraced are appropriate for today as well as the future (http://grcity.us/enterprise-services/officeofenergyandsustainability/Pages/default.aspx/).

Table 2.1: (continued)

Phoenix, AZ; Boston, MA; Philadelphia, PA; and New York, NY	Climate change impacts are being integrated into public health planning and implementation activities that include creating more community cooling centers and neighborhood watch programs, and reducing the urban heat island effect (EPA, 2011; Horton et al. 2012; White-Newsome et al. 2011).
Boulder, CO; New York, NY; and Seattle, WA	Water utilities in these communities are using climate information to assess vulnerability and inform decision-making (EPA, 2010b).
Philadelphia, PA	The City of Philadelphia began a program to develop a green stormwater infrastructure intended to convert more than one-third of the city's impervious land cover to "Greened Acres"– green facilities, green streets, green open spaces, green homes, etc., along with stream corridor restoration and preservation and enhance adaptation to climate change (ORNL, 2012b; www.phillywatersheds.org/ltcpu/).
Cedar Falls, IA	The City of Cedar Falls, Iowa passed legislation that includes a new floodplain ordinance that expands zoning restrictions from the 100-year floodplain to the 500-year floodplain, because this expanded floodplain zone better reflects the flood risks experienced by the city during the 2008 floods (www.epa.gov/dced/pdf/iowa_ climate_adaptation_report.pdf).
Tulsa, OK	Tulsa, Oklahoma has a three-pronged approach to reducing flooding and managing stormwater: (1) prevent new problems by looking ahead and avoiding future downstream problems from new development (e.g., requiring on-site stormwater detention); (2) correct existing problems and learn from disasters to reduce future disasters (e.g., through watershed management and the acquisition and relocation of buildings in flood-prone areas); and (3) act to enhance the safety, environment, and quality of life of the community through public awareness, an increase in stormwater quality, and emergency management (www.smartcommunities.ncat.org/articles/ rooftop/program.shtml).
Western Adaptation Alliance	Western Adaptation Alliance is a group of 10 cities in four states in the Intermountain West that share lessons learned in adaptation planning, develop strategic thinking that can be applied to specific community plans, and join together to generate funds to support capacity building, adaptation planning, and vulnerability assessment (http://sustainablecommunitiesleadershipacademy.org/workshops/ regional-western-adaptation-alliance).

Source: Modified from Bierbaum et al. 2012

The report, "Implementing climate change adaptation: lessons learned from ten examples" (Headwaters Economics, 2012), highlighted primary lessons from ten cities and counties across the United States including Boulder (Colorado), Chicago (Illinois), Chula Vista (California), Eugene (Oregon), Keene (New Hampshire), Miami-Dade County (Florida), New York City, Olympia (Washington), Portland (Oregon), and Taos (New Mexico), as an attempt to inform and inspire other communities in regards to climate adaptation planning and actions. Primary concerns from the cases included recognition of potential threats, local knowledge, values and capacity; integration with existing processes, institutions and economy; and involvement of local actors or stakeholders (Headwaters Economics, 2012).

Several other evidence-based (qualitative and quantitative) studies (e.g. surveys and reviews) on climate adaptation and adaptation planning in cities have been conducted across regions and sectors (e.g. Heinz Center, 2007) that highlight available adaptation planning guidebooks and frameworks, as well as adaptation planning underway in western developed countries. The Heinz Center (2007) survey also provides a roadmap to some of this information as well as a benchmark for information or knowledge sharing on lessons-learned across adaptation community types. Whereas most of the adaptation planning initiatives are government-led, there is evidence of private sector and NGO engagement in various activities that include "planning guidance, provision of implementation tools, contextualized climate information, exchange platforms for best practices and bridging the science-policy gap across sectors" (Bierbaum et al. 2012:11).

What emerges from recent studies (e.g. Bierbaum et al. 2012 and Carmin et al. 2012b) is that a considerable number of cities worldwide and particularly in North America are taking actions to adapt to climate change and related extreme events (via planning or implementation) using a variety of qualitative and quantitative methodologies and tools (including case studies and analogue analyses, scenario analyses, and sensitivity analyses). Although, there is evidence of similarities in approaches (such as mainstreaming or integrating adaptation plans into existing planning and decision-making) there are no "one-size-fits-all" adaptation strategies emerging across scales and sectors, and thus cities are more likely to pursue no- and low-regrets strategies (Bierbaum et al. 2012).

Numerous peer reviewed publications have shown that some barriers exist in adaptation planning process including lack of funding and investment, policy and institutional "bottlenecks,' uncertainty in climate information and fragmented decision-making that have contributed to both limited or lacking implementation and evaluation of adaptation planning actions (Bierbaum et al. 2012; Biesbroek et al. 2013; Carmin et al. 2012b; Lehmann et al. 2012; Measham et al. 2011; Moser and Ekstrom, 2010; 2012). However, evidence to-date supports the notion that information sharing on best practices and learning are greatly aiding adaptation progress across scales and sectors (Preston et al. 2010).

2.5 Drivers of adaptation planning initiatives

Urban local governments manage a wide range of social systems and natural resources (land and water) that are particularly sensitive to the effects of changing climate such as sea-level rise and related extreme flooding events (Poyar and Beller-Simms, 2010). As a result a number of projects have been initiated that minimize the impacts of sea-level rise and extreme flood events on urban social-ecological systems, ensuring that local communities have adaptation response measures and strategies such as flood defenses and early warning systems in place (Carmin et al. 2009).

However, it is widely accepted that social, economic and political drivers, as well as local structures (such as access to decision-making and the structure of social networks and relationships) in most cases function across different scales to facilitate or constrain adaptation planning within urban contexts (Adger et al. 2009; Adger et al. 2005; Pelling et al. 2008; Pelling and High, 2005). The most commonly cited drivers of adaptation planning are strong institutions and networks, social learning, access to capital resources, perceived risks and capacity to adapt and diversification (Jain, 2012).

Following the study of cities in the global south conducted by Carmin et al. (2009), it emerged that adaptation planning initiatives, were mainly driven by incentives, information and resources or capacity. In the same vein, Carmin et al. (2012a) argue that exogenous factors (e.g. extreme events, policy regulations and diffusion of information) are dominant motivation for adaptation planning in the long term while endogenous factors that may include local champions or entrepreneurs in addition to incentives, ideas and capacity are short term. Incentives may include perceived threats to natural resources management and conservation (Lehmann et al. 2012), perceived threats to human or social systems (Damm, 2010; Lehmann et al. 2012), expectation of economic benefits (Adger et al. 2005; Carmin et al. 2009; Lehmann et al. 2012), funding, policy, and regulation concerns (Carmin et al. 2012a; Anguelovski and Carmin, 2011).

Perceptions of risks to human and social systems (including residents, property, and transportation infrastructure), and the general economic and development goals of a city may create an incentive to engage in adaptation planning initiatives (Carmin et al. 2009). For instance, perceived risks of sea-level rise, extreme flooding events and disasters (such as Hurricane Sandy) have contributed to cities in North America engaging in climate action planning (Bierbaum et al. 2012). This suggests that the desire to protect property and local populations is likely and important incentive for initiating adaptation planning (Carmin et al. 2009).

Perceptions about economic risks arising out of the potential consequences of changing climate such as sea-level rise and flooding events are among the factors motivating adaptation planning initiatives (Adger et al. 2005; 2009). According to Adger et al. (2009) the identification of potential social and economic benefits of climate change is significant for initiating adaptation planning, so that the communities can obtain maximum beneficial outcomes. Anticipation of economic benefits encourage engagement of urban communities in adaptation activities especially when they are expected to be widely shared among the community (Lehman et al. 2010).

Funding can directly support adaptation or indirectly be an incentive for engaging in urban adaptation planning initiatives (Carmin et al. 2009). For example Carmin et al. (2009) argues that funding from domestic and international sources have been used to directly support adaptation, both in the context of development (e.g. infrastructure) as well as directly for climate adaptation planning initiatives. Funding can also be an indirect force of change, particularly when a financial incentive contains provisions linked to adaptation-related initiatives (Carmin et al. 2009). In addition, adaptation financing can stimulate untapped investment opportunities that may come with developing new markets for climate-friendly technologies (e.g. participation in the carbon farming, sequestration and abatement activities) in urban environments. Carmin et al. (2012a), argue that climate adaptation initiatives are motivated by endogenous factors and sustained as a consequence of local actors taking advantage of opportunities that arise and creatively weaving this emerging agenda into existing goals, plans, and programs.

Evidence emerging from local experiences and scientific knowledge of the potential impacts of climate change has been an influential driver of adaptation planning in cities around the world. The experience of a natural disaster (often floods) frequently led to a perception that natural hazards are occurring with greater frequency and intensity, and that cities are at greater risk of damage from these (Heinrichs et al. 2013). For instance, after learning about climate impacts projected for the global south, and conducting a vulnerability assessment, it became clear that the city of Durban, South Africa and its inhabitants were at risk from climate impacts and that initiating adaptation planning was a pressing issue in addition to reducing green-house gas emissions. Durban is not alone in making strides in advancing adaptation as other cities globally (New York City and Quito, Ecuador, are noteworthy) are also making significant progress in this arena, many without national level support for their work (Carmin et al. 2012a).

Carmin et al. (2012a:19) argue that “with respect to climate adaptation, likely sources of incentives will be national climate regulations and plans as well as sector-based policies, such as coastal regulations”, as these may provide the framework for adaptation responses (e.g. building capacity to adapt) and encourage effective implementation of adaptation actions. For instance, local policies and regulations may use incentives to generate interest or impose requirements and use the threat of sanctions to foster compliance among organizations or individuals (Anguelovski and Carmin, 2011; Biesbroek et al. 2010; Carmin et al. 2009; Urwin and Jordan, 2008).

Adaptation planning initiatives appears to be linked to information and knowledge about the benefits of adaptation and the implications of not adapting to changing climate and related extreme events (Anguelovski and Carmin, 2011; Carmin et al. 2009). The growing awareness and local knowledge of the benefits of adaptation and effects of changing climate risks and related extreme events seems to have catalyzed many local adaptation planning efforts (Heinrichs et al. 2013). For instance, risks and/or vulnerability assessment using downscaled climate models may generate institutional interest in understanding the risks of changing climate and their potential impacts on cities, and developing appropriate local adaptation response options (Heinrichs et al. 2013). Cities that consider climate change issues and adaptation as more important, and those with more information and knowledge about the benefits of adaptation and mitigation, are more likely to engage in adaptation planning initiatives (Carmin et al. 2012a).

However, new information calls for a wider dialogue to enable adjustments of already initiated adaptation plans as well as providing the baseline knowledge for future initiatives (Heinrichs et al. 2013). Most existing adaptation strategies and plans consist of various interrelated and often overlapping elements and require periodic revision, allowing for the consideration of changing circumstances and the availability of new information and knowledge (Heinrichs et al. 2013). Moreover, decision-making systems can gain from being flexible enough to include new information and knowledge regarding changing environmental, social and political conditions (Ford et al. 2011).

Although recent studies such as Anguelovski and Carmin (2011), Biesbroek et al. (2010), and Carmin et al. (2012a) discuss general trends in relation to motivating factors, these studies fail to identify the specific primary factors driving cities to initiate adaptation planning projects across a variety of scales. Understanding how the driving factors of adaptation planning interact across multiple spatial scales of urban areas and how specific factors influence the selection of appropriate adaptation response options, is important to implementing adaptation actions that avoid significant tradeoffs or negative interactions with existing mitigation plans and broader development goals (Barclay et al. 2013).

2.6 Emerging adaptation response options

The adaptation planning process involves identifying, assessing and selecting adaptation options for either responding to the existing and future changing climate risks and related extreme events across a wide range of spatial scales (Adger et al. 2007; Bierbaum et al. 2012; Moser and Ekstrom, 2010; Preston et al. 2010). Adaptation response options may take many forms such as: no regrets, low regrets, win-win and flexible adaptive options and vary depending on the spatial scale of planning and decision horizons (Smith et al. 2011).

According to Smith et al. (2011) the no regrets options are those initiatives that deliver net socio-economic benefits with or without future changes (e.g. enhancing adaptive capacity of urban communities and avoiding building in flood plains). Low regrets are actions with low cost and maximum benefits such as restricting the type and extent of development in flood risk environments (Preston et al. 2010). Win-win options have the desired result of minimizing risk and exploiting potential opportunities but also have other social, environmental, or economic benefits. Win-win options include well-designed rain-gardens and green roofs that have multiple benefits across a range of scales while flexible or adaptive options involve incremental adaptation options over long temporal scales and seek to reduce the risk of maladaptation (occurring when adaptation strategies generate adverse effects) (Noble et al., 2014; UKCIP, 2008).

Assessment and selection of feasible adaptation options is context dependent and may need a range of planning and decision support tools to generate viable adaptation measures and strategies that can be implemented across a range of spatial scales (Wilby and Dessai, 2010).

Arnell (2010) reviewed case studies and found that local factors significantly affect the choice and feasibility of adaptation options and planning decision making.

Despite increased attention to potential adaptation options, there is less understanding of the relationships with the primary factors driving adaptation planning initiatives, their effectiveness, and the likely extent of their actual implementation (Adger et al. 2007; Gregg et al. 2012; U.S. National Climate Assessment, 2013). Some of the adaptation options emerging across a range of scales include enhancing adaptive capacity, conservation and management; infrastructure, planning, and development, and governance and policy (Gregg et al. 2012).

Enhancing adaptive capacity may include institutional reforms to support resilience, locally appropriate regulations (e.g. land use zoning, storm-water management and building codes), vulnerability and impact assessments, new information and knowledge transfer, and development new tools and resources, among others in order to increase their ability to plan, develop, and implement adaptation actions (Gregg et al. 2012; Kettle and Dow, 2014).

Natural resources management and conservation options includes incorporating climate-smart guidelines into restoration; enhancing connected landscapes, climate-proofing local areas, and the reduction of non-climate stressors (e.g. water withdrawals, pollution)) that are likely to be negatively impacted by climate change conditions (Gregg et al. 2012).

Infrastructure, planning, and development options may include identification and assessment of vulnerabilities of urban water resources and communities to climate-related extreme events (such as increased flooding) and develop strategies and measures to protect infrastructure (such as improving existing or designing new infrastructure to withstand the effects of extreme flooding), as well as public health and safety (Gregg et al. 2012; Kettle and Dow, 2014).

Governance and policy options may include strategies and measures such as creating new policies and/or enhancing existing policies and regulations, and supporting governance systems across geo-political scales to support adaptation action addressing transboundary effects of climate change issues. Traversing political and social boundaries requires coordinated policy and planning efforts (Gregg et al. 2012).

Evidence from recent studies indicate that specific adaptation options in the urban settings can potentially interact (positively or negatively) with decision making beyond geo-political boundaries (Gregg et al. 2012). Because of these complex interactions, it is important to better understand the relationships between adaptation response options and driving factors motivating adaptation initiatives across a range of spatial scales.

2.7 Barriers to implementation of adaptation options

Despite the realization of the potential value of urban climate adaptation planning, many barriers still exist that impede implementation of the emerging adaptation response options across spatial scales. Barriers are factors, conditions, and constraints that need to be overcome by planners and decision makers at varying scales from local to global (Moser and Ekstrom, 2010). Understanding the implementation barriers becomes critical in adaptation planning literature; and some recent studies (e.g. Adger et al. 2009; Bierbaum et al. 2012; Biesbroek et al. 2013; Lehmann et al. 2012; Measham et al. 2011; Moser and Ekstrom, 2010; 2012) attempt to answer 'why adaptation options are not implemented as much as expected despite great potential usefulness?'

Moser and Ekstrom (2010) is one of the notable studies that have developed a framework that identifies barriers in three distinct phases and stages – namely the understanding, planning and managing phases of the adaptation process and decision-making (refer to Figure 2.7). According to Moser and Ekstrom (2010) the barriers include inability to detect the problem, difficulty gathering and using relevant information, and clearly defining the problem in the understanding phase; barriers to developing, assessing, and selecting options in the planning phase; and finally barriers to implementing selected options, monitoring outcomes, and evaluating effectiveness in the managing phase. Specifically, barriers to implementing adaptation options were identified to include actors' intent to implement; resources (e.g. knowledge, skill, and finance); governance (including policies and regulations); social constraints (e.g. actor's perception, behavior, and values) and the context of implementation which would include spatial scales (Moser and Ekstrom, 2010).

An in-depth study by Moser and Ekstrom (2012) involved five case studies in California's San Francisco Bay region revealing that although economic barriers are significant, institutional constraints and actors attitudes are the primary barriers to implementation of adaptation options.

Lehmann et al. (2012:2) also developed a simple analytical framework "to understand barriers and opportunities for adaptation planning in cities." In this case they found that information, incentives, and resources were primary barriers to implementation of adaptation options. However, each of the barriers may be dependent upon the natural and socio-economic environment; actor's perceptions, behavior, and values; and the institutional environment (Lehmann et al. 2012).

Bierbaum et al. (2012) in their comprehensive review of climate adaptation in the U.S. also found that primary barriers to implementation of adaptation options included information uncertainties, lack of resources (e.g. human, social and finance), institutional constraints, governance issues (e.g. fragmented decision making), lack of political leadership, and divergent perception of risk, cultures and values.

Evidence from adaptation literature so far indicate that a range of barriers to implementation of adaptation options are focused around deficiencies in information, institutions, inclusion, incentives and finance, and social networks (Biesbroek et al. 2013; Lehman et al. 2012; Measham et al. 2011; Moser and Ekstrom, 2012).

Deficiencies (real or perceived) in local and scientific knowledge (information) as well as inability to access human, social and financial resources can and do constrain successful planning and implementation of adaptation options (Biesbroek et al. 2013; Lehman et al. 2012; Measham et al. 2011; Moser and Ekstrom, 2010).

In the same vein institutional (public and private) weaknesses, lack of coordinated governance (including policies and regulations), divergent actors' perceptions of risks, and certain cultural biases and values can constrain or impede implementation of adaptation options across geopolitical boundaries (Bierbaum et al. 2012; Biesbroek et al. 2013).

Inclusion in decision making also plays critical role in the acceptance and ownership of emerging planning outcomes (Biesbroek et al. 2013). Thus, lack of involvement of public and private actors in the adaptation planning process can and do constrain effective implementation of adaptation options (Biesbroek et al. 2013).

Incentives (e.g. insurance schemes), financing mechanisms, and social networks are also key determinants of adaptation planning initiatives (Lehman et al. 2012; Moser and Ekstrom, 2010). Thus real or perceived disincentives and financial risks arising from the emerging adaptation options can impede their implementation (Lehman et al. 2012; Moser and Ekstrom, 2012).

Since the IPCC fourth assessment report (AR4) (IPCC, 2007), it emerges that a growing body of literature has been developed (e.g. Anguelovski and Carmin, 2011; Carmin et al. 2009; Carmin et al. 2012b; Bierbaum et al. 2012; Biesbroek et al. 2013; Gregg et al. 2012; Heinrichs et al. 2013; Lehman et al. 2012; Measham et al. 2011; Moser and Ekstrom, 2010; Smith et al. 2011) that review of status of adaptation and provide guidance on how enabling conditions for adaptation can be developed to constraints and accelerate more widespread and successful adaptation planning outcomes.

Chapter 3 - Research design and methodology

This chapter details the methods used to conduct this research—with a focus on the systematic review of adaptation planning case studies in the urban context. The systematic review approach provided a means to draw existing evidence from adaptation planning initiatives by subjecting these cases to (1) clearly formulated questions, (2) the use of explicit methods to identify and then critically appraise relevant documents, and (3) a synthesis of both qualitative and quantitative data derived from each individual cases to generate objective and generalizable findings (Berrang-Ford et al. 2011; Ford et al. 2011; Garg et al. 2008).

Unlike traditional narrative reviews which provide limited details regarding the process and specific sources of information (e.g. databases searched and search terms used) systematic reviews are always guided by an explicit and well documented process (including methods and criteria for inclusion and exclusion of individual studies) that seeks to address explicitly articulated research questions (Brooks et al. 2013; Ford et al. 2011; Garg et al. 2008; Munroe et al. 2012). Since the systematic review process is normally specified in advance and documented, bias in the selection of individual studies is reduced and others can critically appraise the judgments made in case study selection, in the collection, analysis, and interpretation of results, and as necessary, in repeating or updating the research in question (EFSA, 2010; Garg et al. 2008). In systematic reviews the relevant information are explicitly synthesized (from both the peer-reviewed and non-peer-reviewed/'grey' documents) to clarify the links between the original research and the reviewers' conclusions; findings are fully reported, irrespective of the statistical significance of the results (Brooks et al. 2013; Ford et al. 2011; Garg et al. 2008; Munroe et al. 2012).

The main goal of this study was to assess whether there are recognizable relationships between primary drivers of adaptation planning initiatives and the selection of emerging adaptation response options related to urban flooding cases across spatial scales. The study hypothesized that there was evidence of association between (a) the primary drivers of adaptation planning initiatives, and (b) the selection of adaptation options.

The systematic review process provided a means for assessing individual adaptation planning case studies via the following four steps: (1) an explicit search of adaptation planning initiatives written in English between 2008 and 2013 from eight online databases, from Google scholar, government reports and Institutional Web portals, and from four bibliographic databases; (2) clear inclusion/exclusion criteria for the individual case studies identified; (3) extraction of information (e.g. geographic location, motivating drivers, emerging response options, funding sources, evaluation status, and project timeframe) from each individual case to create a dataset stored in MS Access database files and MS Excel worksheets; and (4) coding, interpretation, and synthesis of qualitative and quantitative data (as per Brooks et al. 2013; Ford et al. 2011; and Munroe et al. 2012).

The DPSIR-SES framework was utilized to structure and organize information related to primary factors driving adaptation planning initiatives and the emerging adaptation response options for in-depth analysis using logistic regression (Rounsevell et al. 2010). Binary logistic regression is deemed to be suitable for this study since it applies logarithmic transformation of data to provide insight into the relationships between variables in the analysis (e.g. driving factors of adaptation planning and the selection of adaptation options) aimed at estimating the probability of the "absence or presence" of a variable instead of predicting the variable directly as in the case in multiple (linear) regression analysis (Field, 2009; Pallant, 2011).

In this research "adaptation planning initiative" refers to the distinct project or intervention that was analyzed and reported on in a survey, research publication, and/or document while "case study" refers to the specific phenomenon (or case) described in the planning project (Brooks et al. 2013)

3.1 Search strategy

Urban adaptation planning initiatives and case studies were found by searching information sources and electronic databases using the search strategies presented in Table 3.1. The searches encompassed adaptation survey reports, comprehensive reviews, technical documents, and relevant peer-reviewed research published in English between 2008 and 2013 as found in selected online and bibliographic databases and via Google Scholar. The 2008 to 2013 publication timeframe was chosen to capture adaptation planning initiatives after the IPCC fourth assessment report (AR4) (IPCC, 2007), but before the release of IPCC fifth assessment report (AR5) in 2014.

The IPCC AR4 (2007) spurred significant interest in urban adaptation planning initiatives both qualitatively and quantitatively, including research and the development of National Adaptation Plans of Action (NAPAs) and climate change adaptation (CCA) strategies and plans from regional to local scales.

Table 3.1 Sources for information search

Strategy	Source/ database(s)
Keyword search	Climate adaptation knowledge exchange (CAKE) *EBM (Ecosystem-Based Management) Tools* database *FHWA (Federal Highway Administration) Planning Tools* NOAA (National Oceanic & Atmospheric Association) U.S. Environmental Protection Agency (EPA) database IPCC, United Nations, and World Bank databases
Specialist search	Google Scholar (peer reviewed literature, and non-peer-reviewed or “grey” literature). Government reports (for example, the U.S. National Climate Assessment report, 2013). Institutional Web portals (U.S. university websites – with the list of relevant sources determined by selected study documents).
Bibliographic search	Scopus Web of Knowledge (WOK) ScienceDirect JSTOR

Source: Author, 2014

3.1.1 Keyword search

All searches were conducted in English using the key terms shown in Table 3.2, selected to capture relevant research related to adaptation planning for climate change risks (sea-level rise) and related extreme flooding events in the urban context. An asterisk at the end of certain search terms was used to represent wildcard character that allows alternative word endings (e.g. Cit = city or cities) to be captured in the search process. The Boolean operators “AND” and

“OR” were used (as shown in Table 3.2) so that search terms could be accommodated simultaneously in the searched databases (e.g. Munroe et al. 2012; Brooks et al. 2013).

Table 3.2: Key search terms

Key search terms	Climat* OR “Extreme events” OR Flood* OR “Sea-level rise” AND Adapt* OR “Adapt* plan*” OR Resilience AND Urban OR Cit* OR Local OR Community AND Initiative OR Project OR Intervention OR “Case study”

Source: Author, 2014

The search terms were either entered strategically in pairs or individually from each set of search words in Table 3.2 to maximize the search and ensure valuable results. In cases where databases did not accommodate Boolean operators, adaptation planning-related search terms were entered individually.

3.1.2 Specialist search

Searches for specific documents recommended from the databases were conducted mainly from Google scholar using limited range terms from the sets of search terms in Table 3.2. The emerging adaptation documents were compared with returns from databases (e.g. Munroe et al. 2012; Brooks et al. 2013). References returned by Google Scholar search, but not found in the adaptation databases were added to the reference list (e.g. Brooks et al. 2013).

Including grey literature (e.g. non-peer reviewed reports and project documents) obtained from government documents (such as U.S. National Climate Assessment technical inputs) and U.S. universities Web portals was critical to understanding how urban adaptation planning is taking place. This was particularly so for those activities initiated at community and local scales that do not depend on peer-reviewed publications to share their findings (Brooks et al. 2013; Ford et al. 2011; Berrang-Ford et al. 2011; Garg et al. 2008).

3.1.3 Bibliographic search

The bibliographic databases that were searched for documents containing case studies recommended from the author's specialist search include:

- Scopus
- Web of Knowledge (WOK)
- ScienceDirect
- JSTOR

Previous studies and reviews (including Bierbaum et al. 2012; Carmin et al. 2012; Gregg et al. 2012; Heinz Center, 2007) were identified from the bibliographic searches. Some of the studies contained more than one case study reported. Case studies that had been recommended from specialist searches were extracted and examined for inclusion in the final review.

3.2 Study inclusion and exclusion strategy

3.2.1 Primary inclusion/exclusion criteria

The cases identified and retrieved in the search process were assessed by their title and/or abstract and then the full text for relevance to the research question. Case studies were accepted for further review if they met the following primary inclusion / exclusion criteria:

1. The adaptation planning case studies had to be located in North America (U.S. or Canada) and had to have been published (or the document released) after 2007 and before 2014. This captured case studies published after the release of the inaugural IPCC AR4 report (IPCC, 2007) and before the release of IPCC AR5 (IPCC, 2014) reports as per the method used by Ford et al. (2011).
2. The study had to be published either in a recognized online database (e.g. climate adaptation knowledge exchange), climate adaptation survey report (government sector), technical inputs to the 2013 NCA report, or other highly-relevant source associated with either the primary or grey literature (but not secondary sources). Where more than one acceptable document or article referred to the same study, the most recent article was used while the older article was used to fill in any missing information, as per the approach articulated by Brooks et al. (2013).

3. The study provides information focused on specific climate adaptation planning initiatives, defined broadly as any planning or development or community-based project (internally or externally initiated) in which adaptation is the primary aim focused on reducing vulnerability or enhancing adaptive capacity to risks of flooding events in the urban environment.
4. Sufficient information had to be provided about the case study, including a description of the geographical location, factors motivating or facilitating the initiative, details of the development and implementation of the initiative, as well as a discussion of the potential outcomes of the initiative. A study report where the required information was missing or that appeared to be simply an overview, guideline, or project description only was not used for the review (see Table 3.3).

Studies that met the primary inclusion criteria were downloaded for further review, including studies that showed potential for inclusion but needed closer examination to ensure actual relevance. The author (primary reviewer) read the title and/or abstract, and then full articles carefully to determine whether a relevant climate adaptation planning initiative was reported or mentioned and assessed or discussed in some depth within the document at hand. Initiatives that were perceived to strengthen the knowledge base, share in-depth information, improve data gathering or surveillance/forecasting systems, and increase understandings of vulnerability, adaptive capacity, and resilience to climate change were also reviewed.

The full text of the document had to include substantive reporting or discussion of one or more adaptation planning case(s), and was screened according to the secondary inclusion / exclusion criteria noted in Table 3.3—including relevance, study design or category, type(s) of intervention, and study outcome(s).

3.2.2 Secondary inclusion/exclusion criteria

The primary goal for conducting secondary inclusion and exclusion criteria was to assess the relevance of individual case studies, as well as the design, types of interventions addressed, and specific outcomes from the cases.

Table 3.3: Secondary inclusion/exclusion criteria

Criteria	**Inclusion**	**Exclusion**
1. Relevant subjects(s)	Urban flooding risks, flooding events (e.g. along rivers, drainage ways, and low-lying areas due to stormwater runoff), and sea/lake-level rise. Impacts on built environments, people, and sectors (e.g. business, agriculture, transport, water, forestry).	Evidence not related to sea/lake-level rise, flooding risk and events (e.g. air pollution). Evidence focused exclusively on climate impact risks and uncertainty assessments (rather than on adaptation). Evidence focused only on sustainable development and mitigation of climate change (rather than adaptation).
2. Study design	Systematic reviews, comprehensive longitudinal studies, surveys, qualitative and quantitative case-studies of adaptation initiatives.	Articles focused on theories or conceptual frameworks and providing no indication that adaptations were in practice.
3. Types of intervention	Adaptation related regulations, policy or strategy, action plans, guidance document, incentive scheme, design strategy and education action.	No substantial reference to urban communities, built environment, or urban natural resources. Evidence not focused on urban adaptation planning or design.
4. Study outcomes	Adaptation response options discussed, including measures and strategies for policy, practice, education, and behavior change.	No outcomes specified.

Source: Adapted from Brooks et al. (2013); Ford et al. (2011); and Munroe et al. (2012).

3.3 Data extraction and quality assessment

Data extraction and quality assessment of individual case studies were undertaken by the primary reviewer and a sample double-checked by the author's major advisor using a checklist that included information on the following:

- Context — such as sector (development/conservation/transportation/water); geographic setting (country, city, region); and socio-political setting (urban, suburban).

- Case study type, sector, and design — type (academic peer-review, grey literature) and methods (qualitative, quantitative, both).
- Content — evidence of information on driving factors (perceived risks/economic benefits/policy regulation); response options (enhancing adaptive capacity; management and conservation; infrastructure, planning, and development; policy and governance); and evaluation status (evaluated, not evaluated).

Included studies were assessed in detail by the author for specific variables including: geographic location, boundary/jurisdiction, sociopolitical setting, sectors addressed, funding sources, motivating drivers, and information sources for vulnerability assessment and adaptation planning, response options, evaluation status, and project timeframe (see Table 3.4 and checklist shown in Appendix B). Data extracted from selected individual studies was stored in MS Access and MS Excel databases for ease of reference and further analysis.

Table 3.4: Categories of information used in quality assessment and data extraction

Information Variable	**Examples**
Project location	Region/State/City/Neighborhood
Boundary/Jurisdiction	Regional/State/Community/ Locality
Functional spatial scale	Urban/Suburban
Sector (s)	Development/Conservation/Transportation/Water
Funding sources	Government/ Private/ Foundation
Motivating drivers (driving factors motivating adaptation planning)	Economic benefits; threats to human & social systems; threats to management and conservation; information & knowledge; policy regulation; other.
Adaptation response options, measures, and strategies	Enhancing adaptive capacity; conservation and management; infrastructure, planning, and development; governance & policy
Information sources adaptation planning	Peer reviewed papers; reports; expert knowledge.
Project outcomes	Success, failure, or other
Evaluation status	Evaluated, or not evaluated
Project timeframe	Years

Source: Author, 2014

Quality assessment was based on relevance (external validity) with respect to the review questions and reliability (internal validity) in the selection of individual case studies (Pullin et al. 2013; Wells and Littell, 2009). Following discussion with the Ph.D. committee in December 2013, doubts about the relevance of certain cases were resolved by discussion and agreement with the author's Ph.D. committee chair (similar to Pullin et al. 2013). If data was missing in main publications, information was derived from other published articles reporting on follow up data on the specific study.

To ensure validity of the case studies with respect to the review questions, case study reports for which more than approximately one-third of needed data were missing were discarded (Brooks et al. 2013). Since there was little variation in the quality of adaptation planning cases in the database, this study did not use a quality assessment ranking to weight the projects in the analysis.

Reliability in this context concerns the extent to which selection of case studies for review are consistent over time, and thus minimize bias in the inclusion case studies in the final analysis (Wells and Littell, 2009). In keeping with Oremus et al. (2012), test-retest reliability was assessed by the primary reviewer using Cohen's kappa (k)[9] values to determine the level of consistency of the primary reviewer's decisions regarding the selection (inclusion/exclusion) of individual case studies.

The primary reviewer re-assessed the selected case studies at an interval of two (2) months after the first reliability screening to minimize the potential that the immediate recall of the author's first inclusion/exclusion screening would influence the second screening. The Cohen's kappa (k) values associated with the test-retest reliability assessment were calculated and interpreted as follows: >0.80 was very good, 0.61 - 0.80 was good, 0.41 - 0.60 was moderate, 0.2 - 0.40 was fair and <0.21 was poor (Oremus et al. 2012; Wells and Littell, 2009).

[9] Cohen's Kappa is a common technique for estimating independent rater agreement of raters screening titles during the process of completing a systematic review. Kappa is a coefficient that represents agreement obtained between two raters beyond expected by chance alone. A value of 1.0 represents perfect agreement. A value of 0.0 represents no agreement (Crewson, 2005).

3.4 Variables of interest

The two key categories of variables that were coded (see Appendix C) and marked for further analysis are adaptation response options (dependent variable) and driving factors for adaptation planning initiatives (independent variables) as shown in Table 3.5. The extracted case specific information was used to create a dataset stored in MS Excel worksheet (Appendix D).

On the analysis table (please refer to a copy of the MS Excel worksheet in Appendix D) the presence or absence of a variable is presented by binary numbers '1' and '0'—where "0" is the absence and "1" the presence of the corresponding variable. Each selected case study was examined in regards to the dependent and independent variables noted in Table 3.5 and discussed in sections 3.4.1 and 3.4.2 below.

Table 3.5: Dependent and independent variables

Dependent variables (Adaptation response options)	**Independent variables (Driving factors for adaptation planning projects)**
Enhancing adaptive capacity	Access to new information or knowledge
Natural resource management & conservation	Anticipation of economic benefits
Infrastructure planning & development	Perceived threats to management & conservation
Governance & policy	Support to human or social systems
	Funding & other economic opportunities
	Evidence of climate change effects
	Policy and regulation concerns
	General concerns

Source: Author, 2014

3.4.1 Independent variables: Primary factors driving adaptation planning initiatives

Access to new information and knowledge (NIK): Assessed if new knowledge, ideas, information, or innovations were the likely inducement for an adaptation planning initiative. In other words if adaptation planning initiatives were motivated by information and awareness (scientific or local knowledge) about the current or potential implications of changing climate (and related extreme events), and adaptation (Anguelovski and Carmin, 2011; Carmin et al.

2009; Heinrichs et al. 2013). According to Carmin et al. (2012b), several cities (e.g. New York City, U.S.; Durban, South Africa; and Quito, Ecuador) initiated adaptation planning projects after conducting vulnerability assessments and learning about their risks to projected climate impacts.

Anticipation of economic benefits (ECB): Assessed whether or not current or future economic benefits (e.g. energy efficiency) were the focus of an initiative. The identification of current or future economic benefits may strongly influence initiation of adaptation planning so that the urban communities can obtain maximum beneficial outcomes (Carmin et al. 2009; Foster et al. 2011). Anticipation of economic benefits often encourage engagement of urban communities in adaptation activities, especially when they are expected to be widely shared among the community (Tompkins and Adger, 2004; Lehman et al. 2010).

Perceived threats to management and conservation of natural resources (MAC): Assessed whether or not the perceived risks to management and conservation of urban natural resources (such as watersheds and freshwater resources, including water quality and availability) were the primary concerns driving adaptation planning initiatives. In other words, were the cities engaged in adaptation planning seeking to manage and preserve urban ecosystems as a means to minimize the impacts of natural disasters, ensure that local communities have flood defenses and early warning systems in place, and/or improve or provide reserves for food, water, and safety provisions (Tompkins and Adger, 2004; Carmin et al. 2009)?

Support to human and social systems (HSS): Assessed if initiatives were driven by the need to protect human or social systems (e.g. quality of life, public health, and cultural values) and/or to promote the resilience of urban systems in relation to the existing or potential risks of changing climate and related flooding events, (Carmin et al. 2012a). In other words, this variable or area of concern assesses whether or not the perceptions of the presence of existing or future threats to residents, property, transportation infrastructure, and the general development goals of a city, or the expressed desire to protect property and local populations may have created an incentive for cities to engage in adaptation planning initiatives (Carmin et al. 2009).

Funding and other economic opportunities (FEO): Assessed if funding and/or future investment opportunities were the incentive for adaptation planning efforts. This included projects initiated as a result of available or potential funding (direct or indirect) from domestic and international sources. Funding can directly support adaptation or indirectly be an incentive for engaging in urban adaptation planning initiatives (Carmin et al. 2009). For example, funding from domestic and international sources have been used to directly support adaptation, both in the context of development (e.g. infrastructure creation) as well as directly for climate adaptation initiatives. In addition, as per Anguelovski and Carmin (2011) this variable also includes adaptation financing directed towards untapped investment opportunities (which may come when developing new markets for climate-friendly technologies such as participating in carbon sequestration and abatement activities in urban environments).

Evidence of climate change effects (ECE): Assessed if an initiative was the result of climate change effects such as sea-level rise, flooding, more intense hurricanes, heat waves, intense periods of drought, or other severe impacts. This included initiatives influenced by evidence from local experiences of the impacts of climate change (Carmin et al. 2012a).

Policy and regulation (PAR): Assessed if an initiative resulted from a policy change or regulation, or was focused on introducing policy change or regulations. Policy and regulations at global and national levels may inspire local policies, enable local authorities, fund local activities, or govern local policies by authority (Anguelovski and Carmin, 2011; Biesbroek et al. 2010; Urwin and Jordan, 2008). Local policies and regulations may also impose requirements and use sanctions to foster compliance (or incentives to generate interest) among organizations or individuals to adapt (Carmin et al. 2009; Djordjevic, et al. 2011; Wise et al. 2014).

General concerns (GEN): Assessed whether or not an initiative was characterized by the growing general interest in climate variability and frequency of extreme events (e.g. flooding) issues and the need to build long term resilience of urban communities focusing on either "no-regrets"[10] or "low regrets"[11] actions that would provide multiple benefits and would be good to do for reasons beyond climate adaptation (Poyar and Beller-Simms, 2010).

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[10] A "no regrets" action provides benefits in current and future climate conditions even if no climate change occurs.

[11] "Low regrets" preparedness actions provide import ant benefit s at relatively little additional cost or risk, again regardless of whether the projected climate change occurs.

3.4.2 Dependent variables: Adaptation response options

Enhancing adaptive capacity (AC): Assessed if an initiative considered enhancing adaptive capacity as an option through institutional reforms to support resilience, locally appropriate regulations (e.g. land use zoning, stormwater management and building codes), vulnerability and impact assessments, new information and knowledge transfer, and develop new tools and resources, among others in order to increase their ability to plan, develop, and implement adaptation actions (Gregg et al. 2012; Kettle and Dow, 2014).

Natural resource management and conservation (MC): Assessed whether or not an initiative considered urban natural resource management and conservation as an option to decrease their vulnerability and increase resilience across spatial scales. This is deemed to be important since cities may incorporate "climate-smart" guidelines into restoration; enhance connected landscapes, seek to climate-proof local areas, and/or seek to reduce non-climate stressors (e.g. water withdrawals, pollution) that are likely to interact with climate change impacts (Tompkins and Adger, 2004; Gregg et al. 2012).

Infrastructure, planning, and development (IPD): Assessed if an initiative considered infrastructure, planning and development as an option for addressing the effects of changing climate and the risks of flooding events. Relevant cases required identification and assessment of vulnerabilities of urban water resources and communities to climate-related extreme events (such as increased flooding) and developed strategies and measures to protect infrastructure (such as improving existing or designing new infrastructure to withstand the effects of extreme flooding), and public health and safety (Gregg et al. 2012; Kettle and Dow, 2014).

Governance and policy (GP): Assessed if an initiative considered governance and policy as viable options to addressing transboundary effects of climate change issues that traverse political and social boundaries that required coordinated policy and planning efforts. In such cases response strategies included creating new and enhancing existing policies and regulations; and governance systems across geo-political scales for supporting adaptation actions (Gregg et al. 2012, Urwin and Jordan, 2008).

3.5 Data synthesis and presentation

This section provides details of descriptive (narrative) and quantitative synthesis of the evidence extracted from the individual included studies. Quantitative synthesis was conducted using descriptive statistics and bivariate and multivariate analyses supported by the statistical package for social scientists (SPSS 22.0) that explored the evidence base in relation to the guiding questions of the present study.

3.5.1 Descriptive statistical analysis

Descriptive statistics were used to summarize characteristics of included studies provided in Table 3.6, trends and frequencies of articles reviewed, percentages of missing values, and quality and reliability assessments. Table 3.6 outlines the main categories of the data that were analyzed and subsequently summarized in graphs and charts to provide an overview of the status of adaptation planning initiatives in the United States and Canada, including the associated evidence of the characteristics of individual case studies eligible for review.

Table 3.6: Categories of data to be included in the data analysis

Category	**Specific data**
Projects background	Funding sources Boundary/jurisdiction (spatial scale) Sector addressed Motivating or facilitating factors Emerging adaptation options
Project implementation	Timeframe Information sources for adaptation planning Project status (e.g. evaluated or not evaluated)
General document information	Document title Document type (e.g. survey or published research) Publication year Author and/or affiliation Geographic location (state/region/city)

Source: Author, 2014

Data quality and reliability assessment relied on descriptive statistics in deriving Cohen's kappa (k) values to determine the level of agreement and consistency of decisions regarding the selection (inclusion/exclusion) of individual case studies between the review time periods (Oremus et al. 2012). Likewise, multicollinearity (i.e. high intercorrelations among variables) tests also used descriptive statistics to determine which independent variables were highly correlated across case studies by calculating the variable inflation factors and tolerance statistics (Field, 2009; Pallant, 2011).

3.5.2 Bivariate analysis

The purpose of bivariate analysis was to explore the significant associations between independent variables (driving factors motivating adaptation planning initiatives) and the dependent variables (emerging adaptation response options) in order to determine the key variables for logistic regression analysis (Brooks et al. 2013; Ford et al. 2011; Munroe et al. 2012; Pallant, 2011).

Bivariate analysis was performed using Chi-square (X^2) statistics (Phi coefficient and Cramer's V) analyses in order to signify the statistical strength of association between each the independent variables (primary factors driving adaptation planning initiatives) and the dependent variables (emerging adaptation response options) at 5 percent ($p = 0.05$) or 10 percent ($p = 0.1$) significance levels (Field, 2009; Pallant, 2011).

The main feature of using Phi coefficient and Cramer's V is that the correlation coefficient will almost certainly lie between 0 (no relationship between the two variables) and 1 (a perfect relationship), whereas the closer the coefficient is to 1, the stronger the relationship, the closer it is to zero, the weaker the relationship as shown in Table 3.7 (Rae and Parker, 1992).

The coefficient will be either positive or negative, indicating the direction of a relationship, while the significance level of 5 percent ($p = 0.05$) or 10 percent ($p = 0.1$) means that the findings have a chance of either 5 percent or 10 percent of not being true (Pallant, 2011). However, Cramer's V was preferred for evidence of association as it provides the absolute value of Phi coefficient, in accordance with Rae and Parker (1992) conventions for describing the magnitude of association.

Table 3.7: Phi and Cramer's V contingency table

Value of Phi or Cramer's V	Description
.00 and under .10	Very weak association
.10 and under .20	Weak association
.20 and under .40	Moderate association
.40 and under .60	Relatively strong association
.60 and under .80	Strong association
.80 to 1.00	Very strong association

Source: Rae and Parker, 1992

Adaptation response options entered as dependent variables in the analysis included: enhancing adaptive capacity (AC), natural resources management and conservation (MC), infrastructure, planning, and development (IPD), and governance and policy (GP). Driving factors motivating adaptation planning initiatives entered as independent variables include: access to new information or knowledge (NIK), anticipation of economic benefits (ECB), perceived threats to natural resources management and conservation (MAC), support to human or social systems (HSS), perceived funding and other economic opportunities (FEO), evidence of climate change effects (ECE), policy and regulation (PAR), and general concerns (GEN).

The data was then cross-tabulated and using Chi-square (X^2) statistic (Phi coefficient and Cramer's V) analyses significant association were computed between the primary factors driving adaptation planning initiatives (independent variables) and the emerging adaptation response options (dependent variables) at 5 percent ($p = 0.05$) or 10 percent ($p = 0.1$) significance levels (Field, 2009; Pallant, 2011). The Chi-square test, Phi and Cramer's V coefficients results were interpreted concurrently to provide an indication of significant associations between the variables related to primary factors driving adaptation planning initiatives and adaptation options in accordance with hypothesis that:

H_1: There is evidence of association between primary factors driving adaptation planning and the selection of adaptation response options across scales. Thus, knowledge of primary driving factors can be used to predict adaptation response option (s).

The Chi-square test, Phi coefficients and Cramer's V analyses results were further supported by interpretation focused on Goodman and Kruskal's Tau results that calculated the proportional reduction in error (PRE). The tau statistic is a measure (ranging from 0 to 1), where the number one (1) represents certainty of the extent that knowledge of the independent variable improves the prediction of the dependent variable.

Multicollinearity (i.e. high intercorrelations among variables) tests were conducted utilizing the SPSS Collinearity diagnostics—tolerance and variance inflation factor (VIF)—to determine which independent variables are highly correlated across case studies (Field, 2009; Pallant, 2011). Ideally the independent variables will be strongly related to dependent variables but not strongly related to each other (Field, 2009; Pallant, 2011).

Per Pallant: "Tolerance is an indicator of how much of the variability of the specified independent is not explained by the other independent variables in the model... and is calculated using the formula 1–R squared for each variable…. If this value is very small (less than .10) it indicates that the multiple correlation with other variables is high, suggesting the possibility of multicollinearity" (2011: 158). The VIF is the inverse of the tolerance value and measures the inflation of the variances of coefficients due to collinearity that may exist among independent (Field, 2009; Pallant, 2011). "VIF values above 10 would be a concern here, indicating multicollinearity" (Pallant, 2011: 158).

3.5.3 Multivariate analysis

Multivariate analyses was performed using binary logistic regression since the dependent variables from the review of case studies are dichotomous ("Yes" or "No") signifying their "presence" or "absence" and the independent variables are categorical (i.e. nominal or ordinal), invalidating the assumption of linearity and the use of linear regression (Brooks et al. 2013; Ford et al. 2011; Munroe et al. 2012; Pallant, 2011).

Binary logistic regression was used to examine and understand the relationships that may exist between selected primary factors driving climate adaptation planning initiatives and the selection of emerging adaptation response options across spatial scales in the urban context (Brooks et al. 2013; Ford et al. 2011; Munroe et al. 2012; Pallant, 2011).

The evidence base on adaptation response options and driving factors emerging from a systematic review of adaptation planning initiatives were originally stored in MS excel database as categorical data that take two forms (i.e. presence or absence)—where the values "1 or 0" denotes presence or absence of variables respectively (Field, 2009; Pallant, 2011).

Binary logistic regression is suitable for this study since it applies logarithmic transformation of data on categorical variables aimed at estimating the probability of the "absence or presence" of an outcome variable instead of predicting the variable directly as in the case in multiple (linear) regression analysis (Field, 2009; Pallant, 2011).

The analysis assumes that 'n' independent variables (X_i, X_2, $X_{3 \ldots}$ X_n) are associated with dependent variable (Y), and P is the probability that an event changes, so (1-P) is the probability of no change. The logistic transformation to P is represented as a logarithm of P/ (1-P) denoted as ln [P/ (1-P)] or logit (P).

The logistic regression model is as follows:

$$\boxed{Logit\ \mathrm{P(Y)} = \beta_0 + \sum_{i=1}^{n} \beta_i X_i} \qquad \text{[Equation 3.1]}$$

Also represented as:

$$\boxed{Logit\ P(\mathrm{Y}) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8}$$

Where: P(Y) stand for the probability of presence of adaptation response option; X_i, X_2, $X_{3,}$…, X_n are the primary factors driving adaptation planning initiatives; β_0 is a constant term; β_1 , $\beta_{2 \ldots}$ β_n are partial regression coefficients of the logistic regression, which represent the significance of X on Y or logit P(Y) (Pallant, 2011).

A positive and statistically significant regression coefficient means that the occurrence rate of dependent variable 'logit P(Y)' rises with the increase of independent variable value while a remarkable negative regression coefficient means logit P(Y) occurrence reduces along with the increase of corresponding independent variable (Pallant, 2011).

The backward stepwise (likelihood ratio) regression models were used for examining the significant relationships between the four adaptation response options (namely enhancing adaptive capacity; management and conservation; and improving urban infrastructure, planning, and development) entered as categorical dependent variables and six primary factors driving adaptation planning initiatives (namely, anticipation of economic benefits; perceived threats to urban natural resources management and conservation; support to human or social systems; perceived funding and other economic opportunities; evidence of climate change effects; and improvement of policy and regulation) entered as independent (explanatory) variables (Field, 2009). The backward stepwise method was chosen because it starts with all explanatory variables included in the model, then tests whether any of these variables can be removed from the model without having substantial effect on how well the model fits the observed data (Field, 2009). The approach is selected to avoid omission of important variables in the analysis of each dependent variable (Pallant, 2011).

The model performance was assessed using the Omnibus test, a likelihood ratio chi-square test, which measures how well the models describe the variables at particular significance levels (Pallant, 2011). According to the Omnibus test, a well performing model is indicated by a highly significant value ($p<0.05$) (Pallant, 2011). To support the Omnibus test, the Hosmer & Lemeshaw (H-L) test was used to assess how well the models adjust to data (Field, 2009; Pallant, 2011). A model that adjusts well to data is indicated by significance values greater than five (5) percent ($p>0.05$). The indication of any variations in the dependent variable that is explained by the models were provided by the Cox & Snell R Square and the Nagelkerke R Square values (also known as pseudo R square values that ranges between 0 and 1) suggesting the variability explained by the set of variables (Pallant, 2011).

To provide more intuitive way of interpreting the results, this research estimates the odds ratio for each explanatory variable. The odds ratio indicates the change in the odds (or likelihood) of the dependent variable occurring (i.e. having initiated adaptation planning process), as a result of a unit change in the explanatory variable, ceteris paribus (Field, 2009; Pallant, 2011). In general odds ratio above one (1) indicates that, as the explanatory variable increases, the odds (or likelihood) of the dependent variable occurring also increase (Field, 2009). Conversely an odds ratio below one (1) indicates that, as the explanatory variable increases, the odds of the dependent variable occurring decrease (Field, 2009).

Chapter 4 - Results

Chapter 4 presents the results of the synthesis of data obtained via the systematic review, and discusses these results in relation to the primary question guiding this study: What are the relationships between the primary factors driving adaptation planning initiatives and the selection of the specific adaptation options related to the risk of changing climate and urban flooding events across spatial scales?

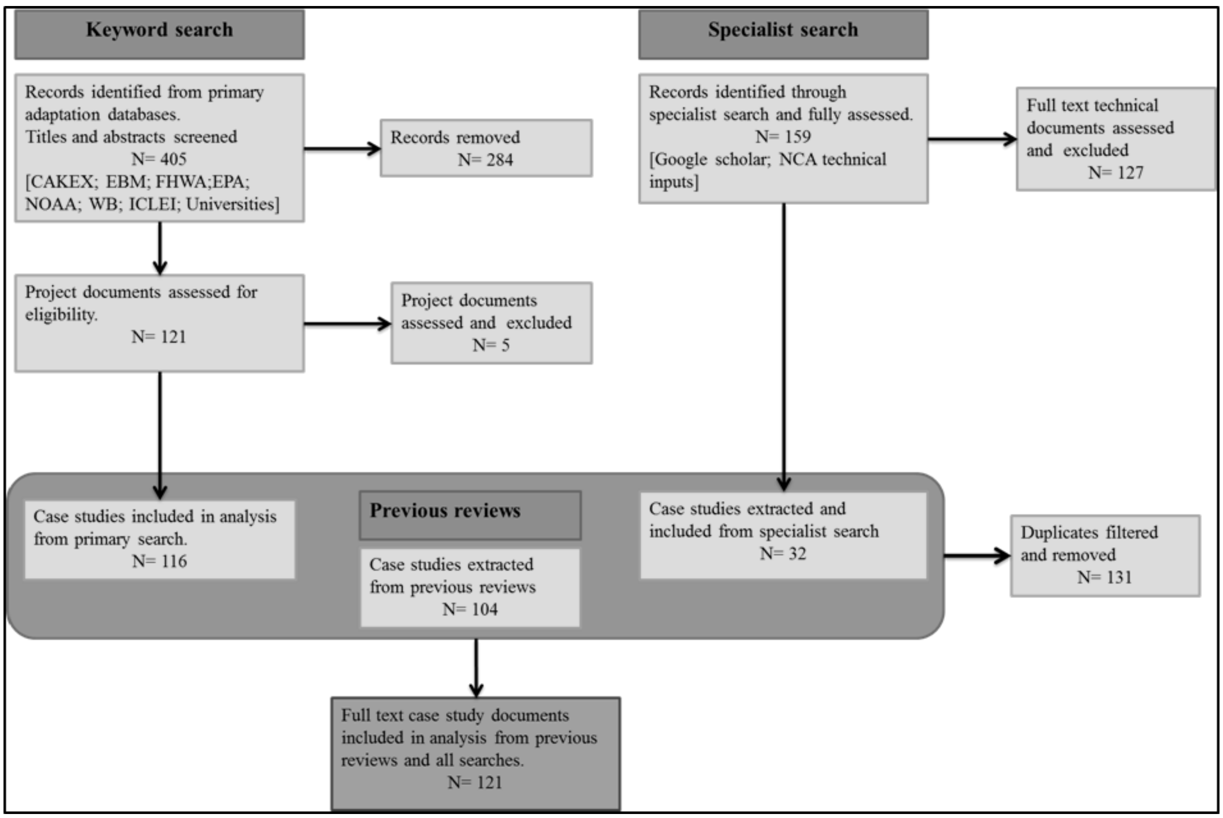
This chapter is organized with respect to the study objectives and hypothesis. First, the study sought to identify the primary factors driving climate adaptation planning initiatives related to risks of urban flooding events. The second objective was to identify emerging adaptation response options for urban flooding risks across a range of cases. The third objective was to explore the relationships between primary factors driving climate adaptation planning initiatives and the selection of adaptation response options related to urban flooding risks across spatial scales. The study hypothesized that there was evidence of association between primary factors driving adaptation planning and the selection of adaptation response options across scales. It was posited that an understanding of primary driving factors could be used to predict the selection of adaptation response options by cities, counties, or other entities.

4.1 Search results

The primary search of adaptation projects databases revealed 405 case studies (Figure 4.1) across urban spatial scales in North America and Canada. Databases used included the following: Climate adaptation knowledge exchange (CAKE); ICLEI (International Council for Local Environmental Initiatives); EBM (Ecosystem-Based Management) Tools database; FHWA (Federal Highway Administration) Planning Tools; NOAA (National Oceanic & Atmospheric Association); U.S. Environmental Protection Agency (EPA) projects database; and IPCC, United Nations, and World Bank databases and other relevant institutional databases. More specific or specialized searches from Google scholar and U.S. National Climate Assessments (NCA) technical inputs produced additional 159 cases for assessment.

The *primary eligibility screening* of titles and abstracts of case studies originally generated by keyword search resulted into inclusion of 121 project documents for *secondary eligibility screening*. Case studies subjected to secondary screening (refer to criteria discussed in the methods section) included 121 case studies from keyword search and 159 cases from specialized search. The secondary screening process generated 116 cases and 32 cases from keyword and specialized searches for inclusion in the final review and analysis. An additional 104 case studies were extracted from previous reviews and survey reports (e.g. Bierbaum et al. 2012; Carmin et al. 2012; Gregg et al. 2012; Heinz Center, 2007).

Figure 4.1: Systematic review map of the search and inclusion process



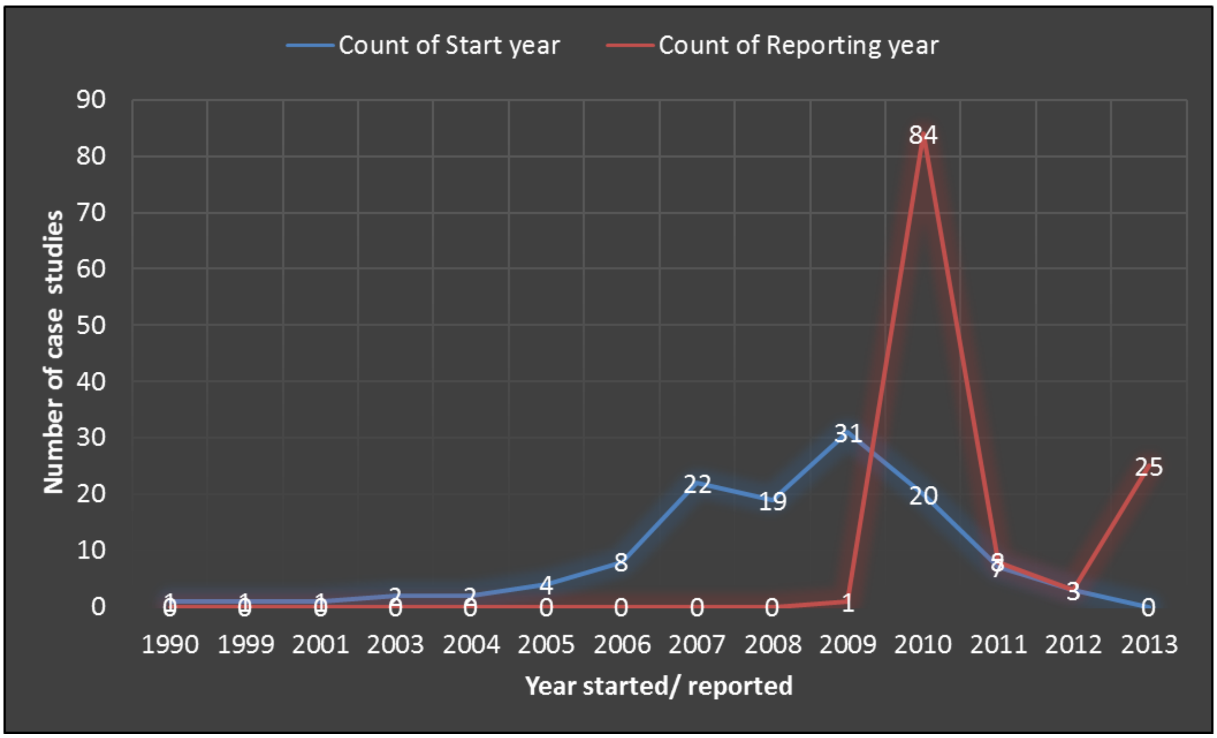
Source: Author, 2014

In total 252 cases satisfied the primary and secondary inclusion criteria for final review and analysis (refer to Figure 4.1). After filtering for duplication the final sample from all searches and previous reviews (including survey reports) was 121 case studies (N=121). A full list of the case studies included in the sample is provided in Appendix A.

4.2 Characteristics of included studies

The number of adaptation planning initiatives focusing on sea-level rise and flooding risk in the urban context increased between 2007 and 2010 (Figure 4.2) at an average rate of 23 cases per year, with 69 percent of the cases reported in 2010. There was a decrease in the number of reported cases between 2011 and 2012, then cases reported began to increase again in 2013.

Figure 4.2: Number of case studies by year started and reported

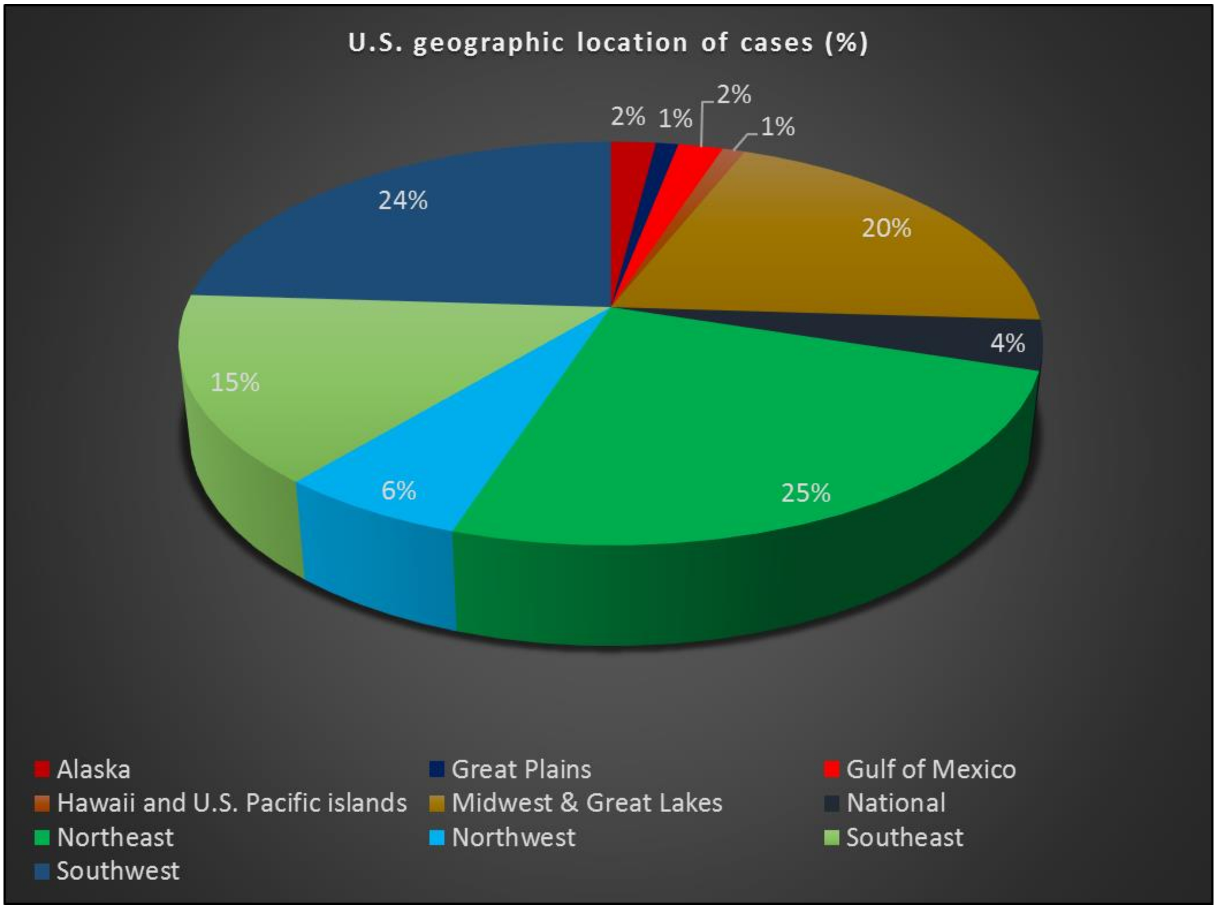


Source: Author, 2014

The adaptation planning initiatives in cities were spatially distributed across 27 states in the United States (N=102) and Canada (N=19) covering either single, cross or multiple boundaries and sectors. The geographic location of case studies is shown in Figure 4.3. Out of the sampled case studies in North America (N=102), approximately 25 percent were located in the Northeast region, nearly 24 percent in Southwest region, 20 percent in the Midwest and Great

Lakes region, 15 percent in the Southeast region, and the rest in Northwest (6 percent), Alaska (2 percent), Gulf of Mexico (2 percent), Great Plains (1 percent) and Hawaii and U.S. Pacific Islands (1 percent). The remaining four (4) percent of the cases addressed adaptation planning in cities from a national perspective.

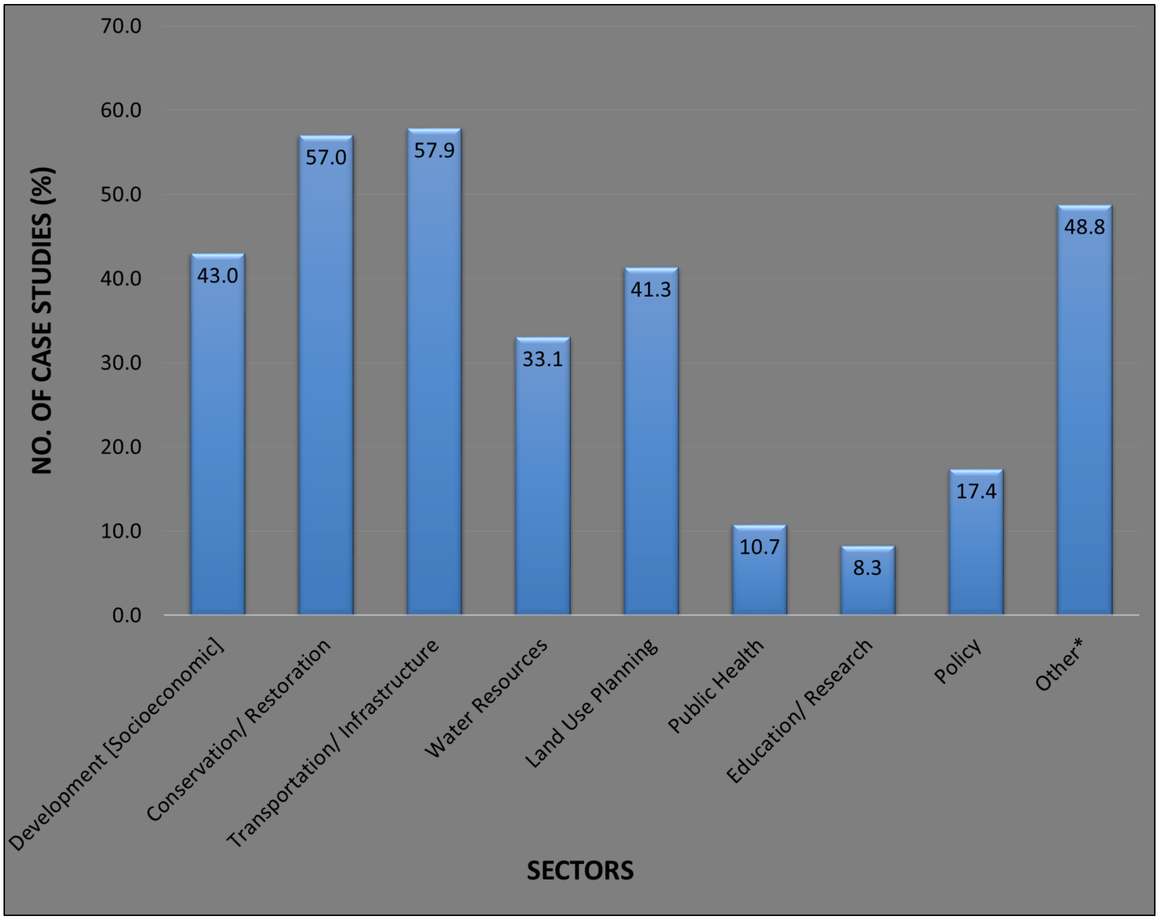
Figure 4.3: Number of case studies by geographic location



Source: Author, 2014

Per Figure 4.4, distribution of urban adaptation planning initiatives by sectors addressed revealed that most of the case studies (58 percent) had a transportation/infrastructure perspective. 57 percent addressed conservation and restoration, while development, land use planning, and water resources sectors were the focus of 43 percent, 41 percent, and 33 percent of adaptation planning cases respectively. Policy (17 percent) and public health (11 percent) were the least addressed sectors by adaptation planning cases. This distribution of cases by sectors may suggest differing priorities of cities in adaptation planning financing or investment across urban sectors.

Figure 4.4: Number of cases by sector(s) addressed

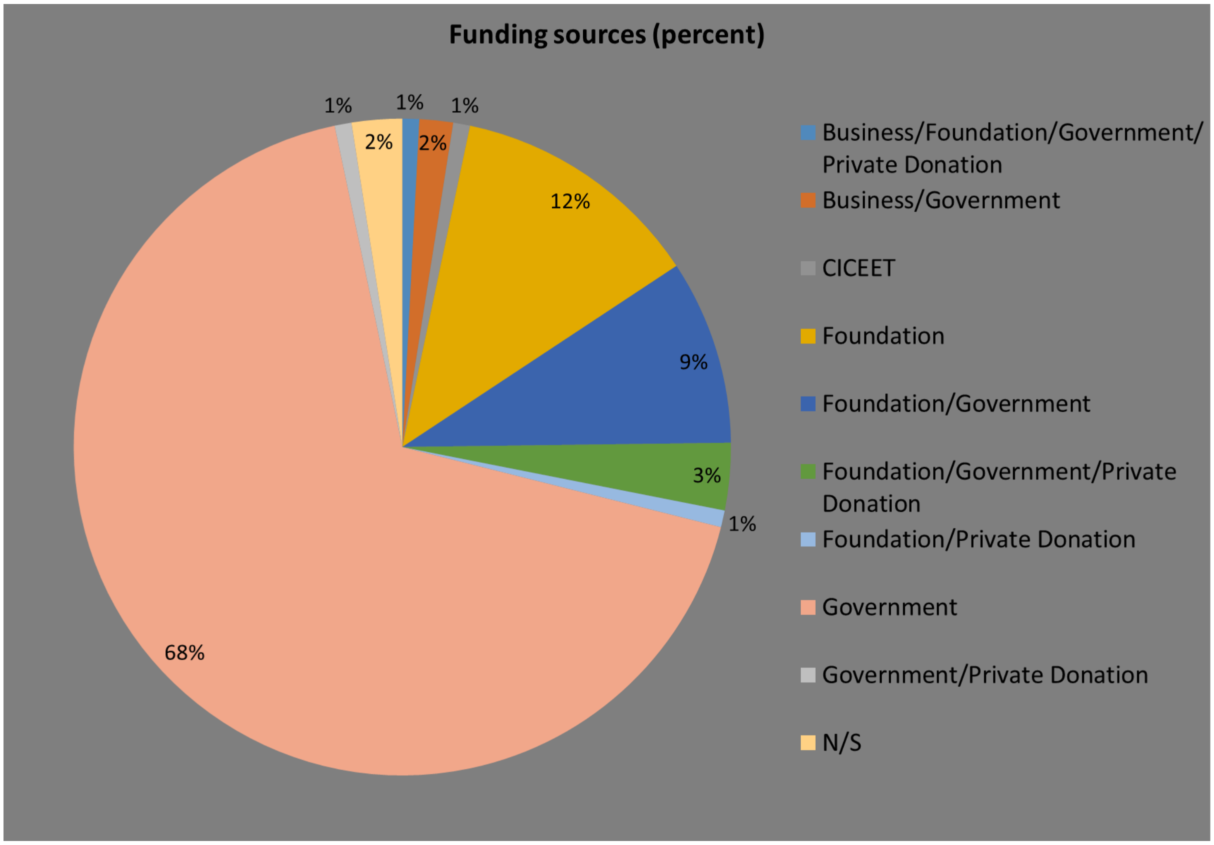


Source: Author, 2014

Government funding appears to be the main source of support for urban adaptation planning projects in North America and Canada (see Figure 4.5). This finding suggests a lack of private investment in an arena that should be of high importance.

Adaptation planning processes for more than 50 percent of the projects examined were supported by scientific expert knowledge. Other information sources included local knowledge (31 percent), published data (26 percent), climate and socioecological models (26 percent), IPCC reports (25 percent), agency and NGO reports (23 percent), peer reviewed literature (22 percent), and management plans (15.7 percent).

Figure 4.5: Number of cases by sources of funding



Source: Author, 2014

4.3 Data quality and reliability assessment

Over 90 percent of the case studies were retrieved from online databases on climate adaptation research such as the Climate Adaptation Knowledge Exchange. Previous reviews (that included Bierbaum et al. 2012; Carmin et al. 2012; Gregg et al. 2012; Heinz Center, 2007) completed rigorous quality assessment and reporting processes. The type of study design and analysis employed by the researchers largely determined the quality of the cases, which means that other biases (such as publication and reporting bias) contributed less to the study quality. Since there was little variation in the quality of adaptation planning case studies in the database, the present study did not use the quality assessment ranking to weight the projects in the analysis.

As previously noted, with regard to reliability in the selection (inclusion / exclusion) of individual case studies, the primary reviewer re-assessed the selected case studies at an interval of two (2) months after the first reliability screening to minimize immediate recall and the potential for the first inclusion / exclusion screening to influence the second screening. The test-retest reliability assessment using Cohen's kappa (k) values, to determine the level of consistency of decisions regarding selection (inclusion/exclusion) of individual case studies returned a statistically significant high level of agreement and consistency (n= 121, k=0.712) between the primary reviewer and the researcher's major advisor (see Table 4.1).

The high level of agreement between the primary reviewer and the researcher's major advisor was influenced by the clear and comprehensive information identified in the summary of case study reports and the primary and secondary inclusion/exclusion criteria discussed in the methodology chapter.

Table 4.1: Test-retest reliability assessment

$Review_{T2}$ * $Review_{T1}$ Cross tabulation

Count

		$Review_{T1}$ Exclude	$Review_{T1}$ Include	Total
$Review_{T2}$	Exclude	12	5	17
	Include	3	101	104
Total		15	106	121

Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Measure of Agreement	Kappa	.712	.096	7.853	.000
N of Valid Cases		121			

a. Not assuming the null hypothesis.

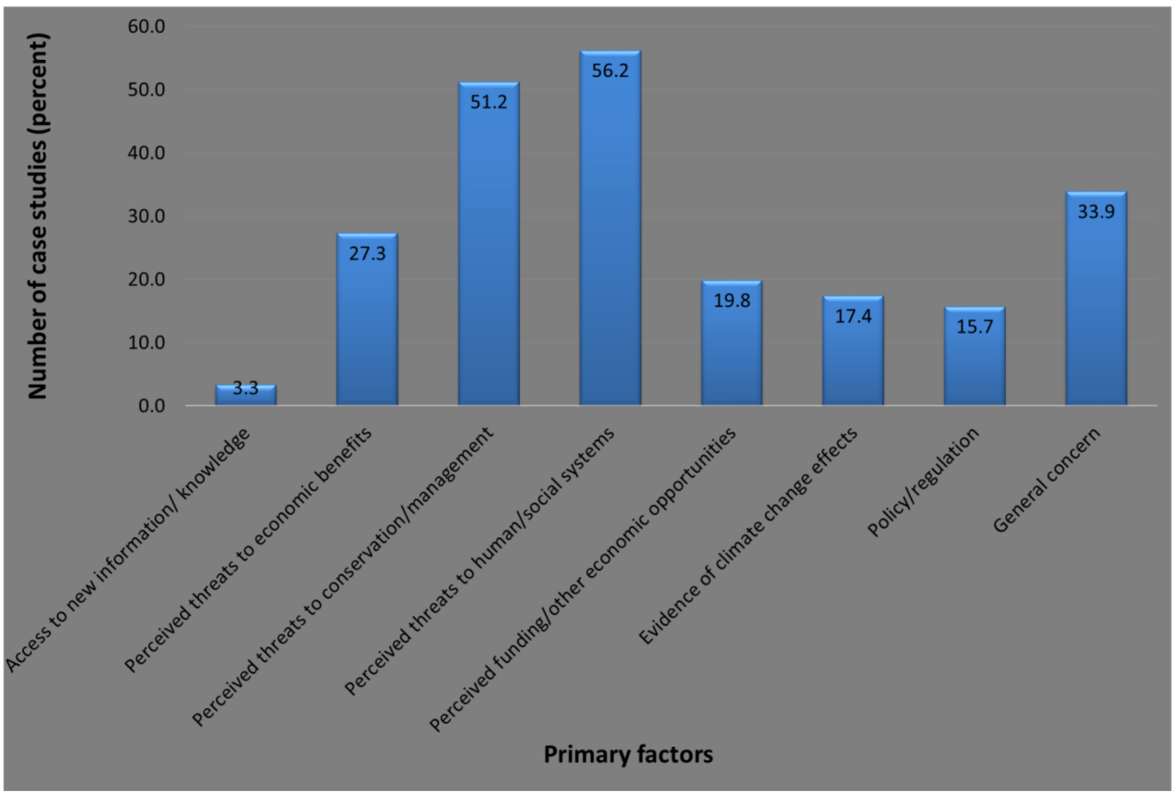
b. Using the asymptotic standard error assuming the null hypothesis.

Source: Author, 2014

4.4 Primary factors driving urban adaptation planning initiatives

This section provides a detailed synthesis of the results addressing the question: what are the primary factors driving climate adaptation planning initiatives related to risk of urban flooding events? The results of descriptive statistics (Figure 4.6) show that adaptation planning projects were mainly driven by perceived threats to human and social systems (56.2 percent), natural resources management and conservation (51.2 percent), and economic benefits (27.3 percent).

Figure 4.6: Primary factors driving adaptation planning initiatives (percent)



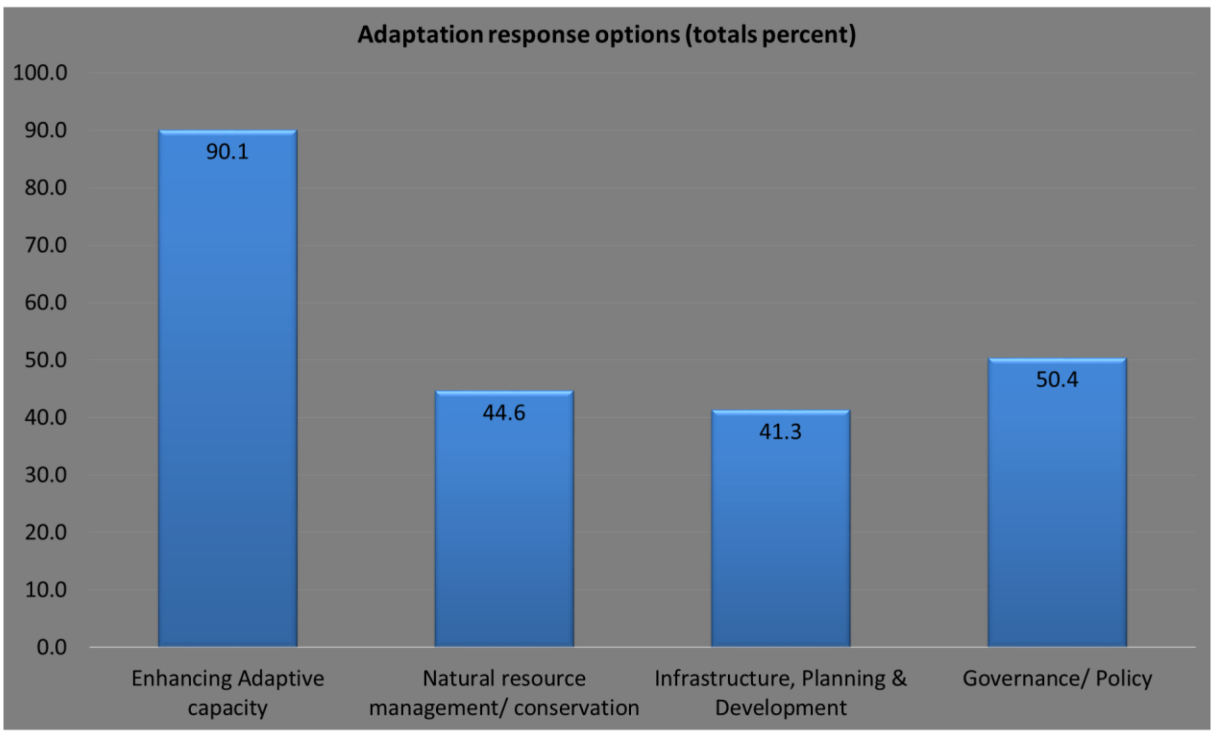
Source: Author, 2014

Other driving factors include perceived funding and investment opportunities (19.8 percent), evidence of climate change effects (17.4 percent), policy and regulations (15.7 percent), and access to information and knowledge (3.3 percent). It is important to note that general concerns (33.9 percent) also features significantly amongst the driving factors of the planning initiatives, which may be attributed to the way some of the cities engage in the "no-regrets" initiatives that deliver net socio-economic benefits with or without future changes in climate or risks of flooding events.

4.5 Emerging adaptation response options

This section provides a synthesis of the main review results addressing the question: what are the emerging adaptation response options related to the risk of urban flooding events across a range of spatial scales? The results of descriptive statistics (Figure 4.7) show that the emerging adaptation response options considered by adaptation planning initiatives across spatial scales were enhancing adaptive capacity (90 percent), governance and policy (50.4 percent), natural resource management/ conservation (44.6 percent), and infrastructure, planning, and development (41.3 percent).

Figure 4.7: Categories of adaptation response options emerging across case studies

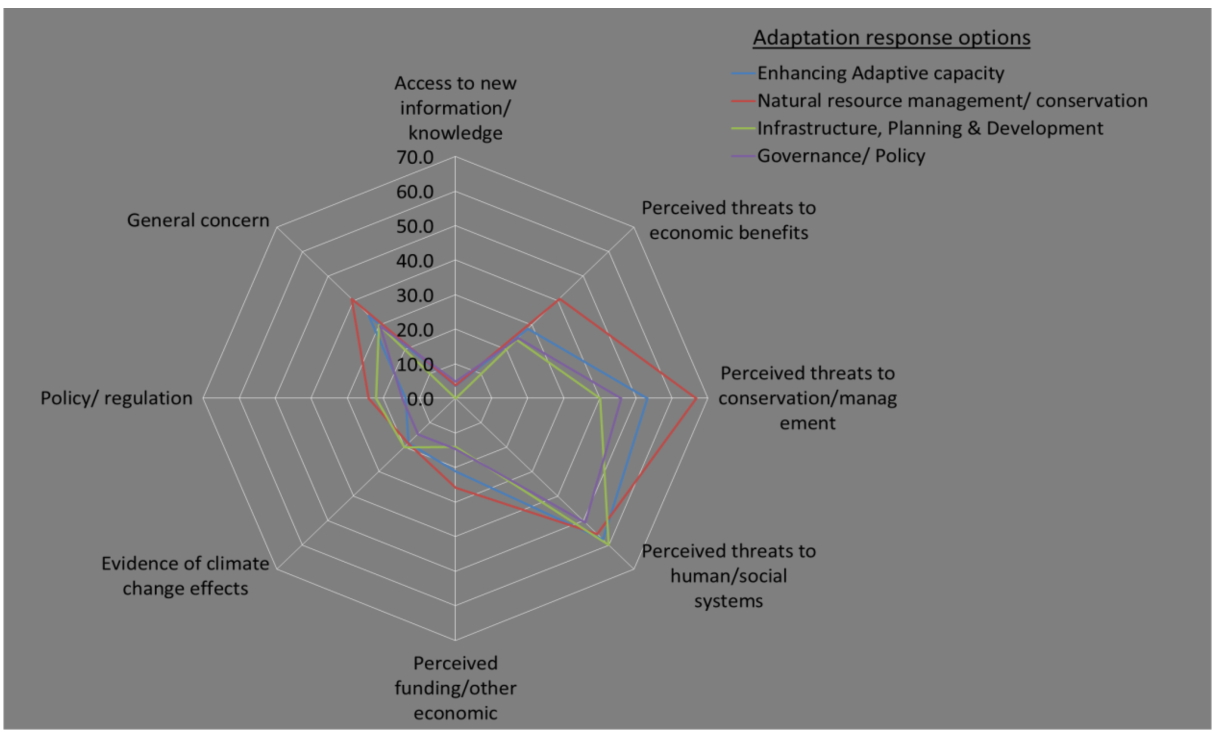


Source: Author, 2014

These results indicate that most of the projects targeted “soft” measures of enhancing adaptative capacity rather than “hard” infrastructure planning and development (which may require high capital expenditures and structural changes).

Descriptive analysis of associations between primary factors driving adaptation planning initiatives and the emerging adaptation response options (Figure 4.8) indicated that adaptation planning projects that reported enhancing adaptive capacity as response option were mainly motivated by perceived threats to human and social systems, management and conservation, and economic benefits. Natural resource management and conservation response options were associated with perceived threats to management and conservation, threats to human and social systems, and economic benefits. Projects that reported infrastructure, planning, and development as a response option were mainly motivated by perceived threats to human and social systems, management and conservation, and economic benefits. Governance and policy response options were reported in projects driven by perceived threats to human and social systems, management and conservation, and economic benefits.

Figure 4.8: Radar diagram for drivers-responses analysis results



Source: Author, 2014

4.6 Relationships between primary factors driving urban adaptation planning initiatives and the selection of adaptation options.

Bivariate analysis was performed using Chi-square (X^2) statistics (Phi coefficient and Cramer's V) analyses in order to signify the statistical strength of association between each the independent variables (primary factors driving adaptation planning initiatives) and the dependent variables (emerging adaptation response options) at 5 percent ($p = 0.05$) or 10 percent ($p = 0.1$) significance levels (Field, 2009; Pallant, 2011).

The results of Pearson Chi-square test, X^2, (1, N=94), Phi and Cramer's V coefficients summarized in Table 4.2 indicated evidence of very weak (Cramer's V= 0.170) to moderate association (Cramer's V= 0.245) between primary factors driving adaptation planning initiatives and selection of adaptation response options at 5 percent ($p = 0.05$) or 10 percent ($p = 0.1$) significance levels.

The results on Table 4.2 indicate that perceived threats to management and conservation of natural resources was significantly associated with the choice of enhancing adaptive capacity (Cramer's V=0.189; p=0.067), management and conservation (Cramer's V=0.225, p=0.030) and, infrastructure, planning, and development (Cramer's V=0.202, p=0.050) options. Perceived threats to human and social systems was only significantly associated with management and conservation (Cramer's V=0.190, p=0.065). Policy and regulation was significantly associated with management and conservation (Cramer's V=0.185, p=0.072) and, infrastructure, planning, and development (Cramer's V=0.191, p=0.064) options. Anticipation of economic benefits was significantly associated with management and conservation (Cramer's V=0.245, p=0.017) while access to new information and knowledge was significantly associated with infrastructure, planning, and development (Cramer's V=0.170, p=0.100) options.

Table 4.2 Pearson Chi-Square test and Phi/Cramer's V coefficients results (N=94)

		NIK	ECB	MAC	HSS	FEO	ECE	PAR	GEN
AC	Pearson Chi-Square	.497[a2]	1.121[a1]	3.358[a1]	2.791[a1]	1.420[a1]	.982[a1]	2.717[a1]	.060[a1]
	Asymp. Sig. (2-sided)	.481	.290	.067	.095	.233	.322	.099	.807
	Fisher's Exact Test	1.000	.485	.084	.133	.443	.448	.113	1.000
	Phi/Cramer's V coefficient	.073	.109	.189	.172	.123	.102	.170	.025
MC	Pearson Chi-Square	.000[a2]	5.650[a]	4.738[a]	3.403[a]	.895[a]	.061[a]	3.232[a]	.389[a]
	Asymp. Sig. (2-sided)	1.000	.017	.030	.065	.344	.804	.072	.533
	Fisher's Exact Test	1.000	.030	.049	.106	.478	1.000	.122	.678
	Phi/Cramer's V coefficient	.000	.245	.225	.190	.098	.026	.185	.064
IPD	Pearson Chi-Square	2.712[a2]	.192[a]	3.850[a]	2.330[a]	1.403[a]	.772[a]	3.427[a]	.235[a]
	Asymp. Sig. (2-sided)	.100	.662	.050	.127	.236	.379	.064	.628
	Fisher's Exact Test	.151	.825	.074	.160	.333	.450	.073	.675
	Phi/Cramer's V coefficient	.170	.045	.202	.157	.122	.091	.191	.050
GP	Pearson Chi-Square	1.334[a2]	.037[a]	.198[a]	.147[a]	1.122[a]	.170[a]	.003[a]	.247[a]
	Asymp. Sig. (2-sided)	.248	.847	.656	.701	.290	.680	.956	.619
	Fisher's Exact Test	.337	1.000	.670	.818	.347	.805	1.000	.680
	Phi/Cramer's V coefficient	.119	.020	.046	.040	.109	.042	.006	.051

a. 0 cells (0.0%) have expected count less than 5.
a1. 1 cells (25.0%) have expected count less than 5.
a2. 2 cells (50.0%) have expected count less than 5.

Source: Author, 2014

In summary the results in Table 4.2 suggest the selection of enhancing adaptive capacity as an adaptation option for urban communities at risk of changing climate and extreme flooding events may be influenced by perceived threats to management and conservation of urban natural resources. In the same vein, anticipation of economic benefits, perceived threats to management and conservation of urban natural resources, the support to human and social systems, and policy regulations may each influence the selection of urban natural resources management and conservation options. The selection of adaptation options related to infrastructure, planning and development may be influenced by access to information and knowledge, perceived threats to management and conservation of urban natural resources, and policy and regulations.

The Chi-square test, Phi coefficients and Cramer's V results were supported further by the interpretation of Goodman and Kruskal's Tau results (Table 4.3). The tau statistic is a measure ranging from 0 to 1, where 1 represents certainty of the extent that knowledge of the independent variable improves the prediction of the dependent variable.

Table 4.3: Goodman & Kruskal's Tau

		NIK	ECB	MAC	HSS	FEO	ECE	PAR	GEN
AC	Tau	.005	.012	.036	.030	.015	.010	.029	.001
	Asymp. Std. Error[a]	.002	.019	.041	.040	.019	.016	.042	.005
MC	Tau	.000	.060	.050	.036	.010	.001	.034	.004
	Asymp. Std. Error[a]	.000	.048	.045	.038	.020	.005	.036	.013
IPD	Tau	.029	.002	.041	.025	.015	.008	.036	.002
	Asymp. Std. Error[a]	.006	.009	.042	.030	.024	.019	.040	.010
GP	Tau	.014	.000	.002	.002	.012	.002	.000	.003
	Asymp. Std. Error[a]	.021	.004	.009	.008	.022	.009	.001	.011

a. Not assuming the null hypothesis.

Source: Author, 2014

The results of Goodman and Kruskal's Tau in Table 4.3 indicate that by having knowledge of primary factors driving adaptation planning one would be making only up to five percent fewer errors when predicting the presence of adaptation options. This can be interpreted to mean weak certainty in prediction, but indicates that some relationship exists.

The relationships of significantly associated variables were therefore examined further using multicollinearity test and multivariate analyses. Multicollinearity was assessed for all independent variables and the results in Table 4.4, indicate tolerance values above 0.1 and VIF values less than 10. The results can be interpreted that multicollinearity was not an issue in this research. Normally, results indicating tolerance values less than 0.1 or VIF values greater than 10 would certainly be an indication of multicollinearity (Field, 2009).

Table 4.4: Collinearity statistics results of independent variables

		NIK	ECB	MAC	HSS	FEO	ECE	PAR	GEN
NIK	Tolerance	1.000							
	VIF	1.000							
ECB	Tolerance	.940	1.000						
	VIF	1.064	1.000						
MAC	Tolerance	.956	.888	1.000					
	VIF	1.046	1.127	1.000					
HSS	Tolerance	.940	.883	.910	1.000				
	VIF	1.064	1.133	1.099	1.000				
FEO	Tolerance	.940	.884	.909	.970	1.000			
	VIF	1.064	1.131	1.100	1.031	1.000			
ECE	Tolerance	.940	.864	.913	.971	.960	1.000		
	VIF	1.064	1.157	1.096	1.030	1.041	1.000		
PAR	Tolerance	.957	.890	.927	.970	.979	.968	1.000	
	VIF	1.045	1.123	1.078	1.031	1.022	1.033	1.000	
GEN	Tolerance	.960	.892	.918	.974	.963	.987	.906	1.000
	VIF	1.042	1.121	1.089	1.027	1.039	1.013	1.104	1.000

Source: Author, 2014

Multivariate analyses was then performed using binary logistic regression to examine and understand the relationships between selected primary factors driving climate adaptation planning initiatives and single emerging adaptation response options. The resulting models show significant relationships between the primary factors driving urban adaptation planning initiatives and the selection of specific adaptation response options for addressing the existing and potential impacts of changing climate and flooding events across spatial scales.

Model result 1: Enhancing Adaptive Capacity (AC) options

The first model examined the relationships between the selected drivers of adaptation planning initiatives and the choice of enhancing adaptive capacity as an option to risks of urban flooding events. The results of Omnibus test, Homer and Lemeshow test, and model summary are presented in Figure 4.9. The Omnibus test indicate satisfactory model performance (X^2 = 7.431, 2df, p = 0.024). The Hosmer & Lemeshaw (H-L) test results (X^2 = 0.681, 2df, p = 0.712) indicate that the goodness-of-fit is satisfactory. The Cox & Snell R Square and the Nagelkerke R Square values are 0.076 and 0.154 respectively suggesting that between 7.6 percent and 15.4 percent of variation in the choice of enhancing adaptive capacity as a response option can be predicted by the model.

Figure 4.9: Omnibus test, Homer and Lemeshow test, and Model summary

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	11.195	6	.083
	Block	11.195	6	.083
	Model	11.195	6	.083
Step 2[a]	Step	-.170	1	.680
	Block	11.025	5	.051
	Model	11.025	5	.051
Step 3[a]	Step	-.737	1	.391
	Block	10.288	4	.036
	Model	10.288	4	.036
Step 4[a]	Step	-.879	1	.348
	Block	9.408	3	.024
	Model	9.408	3	.024
Step 5[a]	Step	-1.977	1	.160
	Block	7.431	2	.024
	Model	7.431	2	.024

a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	4.580	8	.801
2	8.319	8	.403
3	5.584	6	.471
4	3.794	4	.435
5	.681	2	.712

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	52.515[a]	.112	.228
2	52.686[a]	.111	.225
3	53.423[a]	.104	.211
4	54.302[a]	.095	.193
5	56.279[a]	.076	.154

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

Source: Author, 2014

Table 4.5 indicate the significant contribution of each of the selected drivers of adaptation planning initiatives to the decision of selecting enhancing adaptive capacity option. The results show that two variables (MAC, $p = 0.032$; PAR, $p = 0.038$) contribute significantly to the predictive ability of the model. The model results show that perceived threats to natural resources management and conservation (MAC) was significantly and positively related to the choice of enhancing adaptive capacity, whereas policy and regulations (PAR) was related negatively. The odds ratio suggests that urban adaptation planning initiatives driven by perceived threats to natural resources management and conservation were 5.4 (95 % confidence interval: 1.2-25.5, $p = 0.032$) times likely, to consider enhancing adaptive capacity as an adaptation option. This implies that the presence of perceived threats to natural resources management and conservation as the primary factor driving cities to engage in adaptation planning may increase the likelihood for opting to enhance adaptive capacity.

Similarly, the odds ratio suggests that cities driven by policy and regulations to engage in adaptation planning initiatives were 0.2 (95 % confidence interval: 0.0-1.0, $p = 0.038$) times likely to consider enhancing adaptive capacity as an adaptation option. This implies that the presence of policy and regulations as a primary factor may reduce the likelihood for opting to enhance adaptive capacity in relation to the risk of urban flooding events.

These results suggest that planners, policy makers, and investors may be able to predict and make informed decisions about whether or not the choice of enhancing adaptive capacity would be the most viable response option, based on the assessment that particular adaptation planning initiatives were primarily driven by perceived threats to natural resources management and conservation and/or policy and regulations in relation to the risk of changing climate and related urban flooding events. For example, the San Francisco Bay, California project "Adapting to Rising Tides" (http://www.cakex.org/case-studies/case-studies/case-studies/2737) driven by the concerns about the potential impacts of sea-level rise on ecosystems, the economy, and infrastructure opted to engage local communities in vulnerability assessments to enhance their adaptive capacity in the implementation of relevant adaptation options.

Table 4.5: Variables in the equation (enhancing adaptive capacity options)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	ECB(1)	.382	.939	.165	1	.684	1.465	.233	9.225
	MAC(1)	1.395	.818	2.908	1	.088	4.036	.812	20.061
	HSS(1)	.942	.762	1.528	1	.216	2.566	.576	11.431
	FEO(1)	.891	1.124	.628	1	.428	2.437	.269	22.046
	ECE(1)	.881	1.131	.607	1	.436	2.413	.263	22.126
	PAR(1)	-1.518	.844	3.236	1	.072	.219	.042	1.145
	Constant	.764	.695	1.208	1	.272	2.147		
Step 2[a]	MAC(1)	1.495	.787	3.603	1	.058	4.458	.953	20.866
	HSS(1)	1.024	.736	1.940	1	.164	2.786	.659	11.777
	FEO(1)	.950	1.117	.723	1	.395	2.585	.290	23.062
	ECE(1)	.889	1.129	.620	1	.431	2.433	.266	22.237
	PAR(1)	-1.489	.840	3.144	1	.076	.226	.044	1.170
	Constant	.755	.688	1.201	1	.273	2.127		
Step 3[a]	MAC(1)	1.514	.791	3.666	1	.056	4.547	.965	21.427
	HSS(1)	.996	.734	1.842	1	.175	2.707	.643	11.402
	FEO(1)	.948	1.111	.728	1	.393	2.582	.292	22.802
	PAR(1)	-1.553	.833	3.472	1	.062	.212	.041	1.084
	Constant	.925	.646	2.047	1	.153	2.521		
Step 4[a]	MAC(1)	1.576	.788	3.996	1	.046	4.835	1.031	22.667
	HSS(1)	1.034	.725	2.031	1	.154	2.812	.679	11.650
	PAR(1)	-1.654	.829	3.984	1	.046	.191	.038	.971
	Constant	1.070	.634	2.853	1	.091	2.915		
Step 5[a]	MAC(1)	1.692	.789	4.596	1	.032	5.432	1.156	25.521
	PAR(1)	-1.700	.820	4.296	1	.038	.183	.037	.912
	Constant	1.695	.488	12.074	1	.001	5.449		

a. Variable(s) entered on step 1: ECB, MAC, HSS, FEO, ECE, PAR.

Source: Author, 2014

Model result 2: Management and Conservation (MC) options

The second model examined the relationships between the selected drivers of adaptation planning initiatives and the selection of management and conservation options to urban flooding risk and events. The results of Omnibus test, Homer and Lemeshow test, and model summary are presented in Figure 4.10. The Omnibus test indicate satisfactory model performance (X^2 = 14.874, 3df, p = 0.002). The Hosmer & Lemeshaw (H-L) test results (X^2 = 10.434, 5df, p = 0.064) indicate that the goodness-of-fit is satisfactory. The Cox & Snell R Square and the Nagelkerke R Square values are 0.146 and 0.195 respectively suggesting that between 14.6 percent and 19.5 percent of variation in the selection of management and conservation as a response option can be predicted by the model.

Figure 4.10: Omnibus test, Homer and Lemeshow test, and Model summary

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	17.032	6	.009
	Block	17.032	6	.009
	Model	17.032	6	.009
Step 2[a]	Step	-.192	1	.662
	Block	16.840	5	.005
	Model	16.840	5	.005
Step 3[a]	Step	-.847	1	.357
	Block	15.993	4	.003
	Model	15.993	4	.003
Step 4[a]	Step	-1.119	1	.290
	Block	14.874	3	.002
	Model	14.874	3	.002

a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	6.443	7	.489
2	5.162	7	.640
3	8.014	7	.331
4	10.434	5	.064

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	113.280[a]	.166	.221
2	113.472[a]	.164	.219
3	114.319[a]	.156	.209
4	115.438[a]	.146	.195

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Source: Author, 2014

Table 4.6 indicate the significant contribution of each of the selected drivers of adaptation planning initiatives to the decision of considering management and conservation options. The results indicate that three variables (ECB, p = 0.018; MAC, p = 0.058; HSS, p = 0.019) contribute significantly to the predictive ability of the model.

Table 4.6: Variables in the equation (management and conservation options)

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	ECB(1)	1.017	.505	4.060	1	.044	2.765	1.028	7.435
	MAC(1)	.851	.496	2.940	1	.086	2.341	.885	6.190
	HSS(1)	-1.225	.534	5.271	1	.022	.294	.103	.836
	FEO(1)	.481	.531	.822	1	.365	1.618	.572	4.582
	ECE(1)	-.236	.540	.191	1	.662	.790	.274	2.278
	PAR(1)	.680	.593	1.313	1	.252	1.974	.617	6.315
	Constant	-.234	.541	.188	1	.665	.791		
Step 2[a]	ECB(1)	1.001	.502	3.978	1	.046	2.720	1.017	7.273
	MAC(1)	.842	.495	2.887	1	.089	2.320	.879	6.125
	HSS(1)	-1.229	.532	5.347	1	.021	.293	.103	.829
	FEO(1)	.485	.530	.838	1	.360	1.625	.575	4.594
	PAR(1)	.691	.592	1.361	1	.243	1.995	.625	6.369
	Constant	-.278	.530	.275	1	.600	.757		
Step 3[a]	ECB(1)	1.073	.496	4.678	1	.031	2.923	1.106	7.726
	MAC(1)	.836	.492	2.888	1	.089	2.307	.880	6.049
	HSS(1)	-1.207	.526	5.269	1	.022	.299	.107	.838
	PAR(1)	.610	.584	1.092	1	.296	1.841	.586	5.780
	Constant	-.173	.513	.113	1	.737	.842		
Step 4[a]	ECB(1)	1.160	.490	5.598	1	.018	3.188	1.220	8.332
	MAC(1)	.919	.485	3.585	1	.058	2.507	.968	6.492
	HSS(1)	-1.243	.530	5.511	1	.019	.289	.102	.814
	Constant	-.108	.509	.045	1	.831	.897		

a. Variable(s) entered on step 1: ECB, MAC, HSS, FEO, ECE, PAR.

Source: Author, 2014

The results in Table 4.6 show that anticipation of economic benefits (ECB) and perceived threats to natural resources management and conservation (MAC) were significantly and positively related to the selection of management and conservation options, whereas the need for support to human and social systems (HSS) was related negatively. The odds ratio suggests that urban adaptation planning initiatives driven by anticipation of economic benefits and perceived threats to natural resources management and conservation were 3.2 (95 % confidence interval: 1.2-8.3, $p = 0.018$) and 2.5 (95 % confidence interval: 1.0-6.5, $p = 0.058$) times likely to consider selection of management and conservation options respectively. This implies that presence of anticipation of economic benefits and/or perceived threats to natural resources management and conservation as primary factors driving adaptation planning initiatives may increase the likelihood of selecting management and conservation options related to the risk of urban flooding events.

Similarly, the odds ratio suggest that cities driven by the need for support to human and social systems were 0.3 (95 % confidence interval: 0.1-0.8, $p = 0.019$) times likely to select management and conservation options. This implies that the presence of the need for support to human and social systems as the primary factor driving adaptation planning initiatives may reduce the likelihood of selecting management and conservation options in relation to the risk of urban flooding events.

These results suggest that planners, policy makers, and investors may be able to predict and make informed decisions about whether or not the choice of management and conservation options would be the most viable responses, based on the assessment that particular adaptation planning initiatives were primarily driven by the anticipation of economic benefits and/or perceived threats to natural resources management and conservation in relation to the risk of changing climate and related urban flooding events. For instance, the City of Chicago (http://www.chicagoclimateaction.org/pages/adaptation/11.php) and New York City (http://www.nyc.gov/html/dep/html/stormwater/nyc_green_infrastructure_plan.shtml) driven by perceived threats to urban natural resources management and conservation and economic benefits, initiated green infrastructure interventions (such as urban ecosystem restoration, naturalized stormwater management, green roofs, urban forestry, and urban agriculture) that would potentially provide long-term multiple benefits (e.g. reduced energy consumption, decreased stormwater runoff, water capture and conservation, storm-surge protection, and defense against lake- or sea-level rise) critical for combating the impacts of urban flood events, creating healthy built environments, and improving quality of life of the urban communities (Armitage, 2005; Kirshen et al. 2008; Wilby and Keenan, 2012).

Model result 3: Infrastructure, planning, and development (IPD) options

The third model examined the relationships between the selected driving factors motivating adaptation planning initiatives and the choice of infrastructure, planning, and development (IPD) options to urban flooding risk and events. The results of Omnibus test, Homer and Lemeshow test, and model summary are presented in Figure 4.11.

Figure 4.11: Omnibus test, Homer and Lemeshow test, and Model summary

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	15.186	6	.019
	Block	15.186	6	.019
	Model	15.186	6	.019
Step 2[a]	Step	-.464	1	.496
	Block	14.721	5	.012
	Model	14.721	5	.012
Step 3[a]	Step	-1.247	1	.264
	Block	13.475	4	.009
	Model	13.475	4	.009
Step 4[a]	Step	-1.181	1	.277
	Block	12.293	3	.006
	Model	12.293	3	.006

a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	8.557	8	.381
2	5.412	8	.713
3	2.292	7	.942
4	.099	4	.999

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	110.838[a]	.149	.202
2	111.302[a]	.145	.196
3	112.549[a]	.134	.181
4	113.730[a]	.123	.166

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Source: Author, 2014

The Omnibus test indicate satisfactory model performance (X^2 = 12.293, 3df, p = 0.006). The Hosmer & Lemeshaw (H-L) test results (X^2 = 0.099, 4df, p = 0.999) indicate that the goodness-of-fit is satisfactory. The Cox & Snell R Square and the Nagelkerke R Square values are 0.123 and 0.166 respectively suggesting that between 12.3 percent and 16.6 percent of variation in the selection of infrastructure, planning, and development (IPD) options can be predicted by the model.

Table 4.7 indicate the significant contribution of each of the selected drivers of adaptation planning initiatives to the decision of considering infrastructure, planning, and development (IPD) options. The results indicate that three variables (MAC, p = 0.013; HSS, p = 0.09; PAR, p = 0.021) contribute significantly to the predictive ability of the model. The results in Table 4.7 show that the need for support to human and social systems (HSS) and policy and regulations (PAR) were significantly and positively related to the selection of infrastructure planning, and development options, whereas perceived threats to natural resources management and conservation (MAC) was related negatively. The odds ratio suggests that adaptation planning initiatives driven by the need for support to human and social systems and policy and regulations were 2.5 (95 % confidence interval: 0.9-7.3, p = 0.090) and 3.7 (95 % confidence interval: 1.2-11.2, p = 0.021) times likely to consider the infrastructure, planning, and development options respectively. This implies that the presence of the need for support to human and social systems and/or policy and regulations as primary factors driving adaptation planning initiatives may increase the likelihood of selecting infrastructure, planning, and development options related to the risk of urban flooding events. Similarly, the odds ratio suggest that cities driven by perceived threats to natural resources management and conservation were 0.3 (95 % confidence interval: 0.1-0.8, p = 0.013) times likely to consider infrastructure, planning, and development options. This implies that the presence of perceived threats to natural resources management and conservation as a primary driving factor may reduce the likelihood of selecting infrastructure, planning, and development options related to the risk of urban flooding events.

Table 4.7: Variables in the equation (infrastructure, planning, and development options)

Variables in the Equation								95% C.I.for EXP(B)	
		B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Step 1[a]	ECB(1)	-.357	.528	.458	1	.499	.700	.249	1.969
	MAC(1)	-1.241	.505	6.037	1	.014	.289	.107	.778
	HSS(1)	1.044	.577	3.275	1	.070	2.839	.917	8.790
	FEO(1)	-.540	.561	.928	1	.335	.583	.194	1.748
	ECE(1)	.635	.541	1.374	1	.241	1.887	.653	5.451
	PAR(1)	1.382	.598	5.339	1	.021	3.982	1.233	12.856
	Constant	-.619	.563	1.211	1	.271	.538		
Step 2[a]	MAC(1)	-1.283	.499	6.607	1	.010	.277	.104	.737
	HSS(1)	.966	.558	3.000	1	.083	2.628	.881	7.844
	FEO(1)	-.607	.553	1.203	1	.273	.545	.184	1.612
	ECE(1)	.607	.538	1.272	1	.259	1.835	.639	5.265
	PAR(1)	1.288	.578	4.960	1	.026	3.626	1.167	11.268
	Constant	-.614	.557	1.217	1	.270	.541		
Step 3[a]	MAC(1)	-1.274	.495	6.620	1	.010	.280	.106	.738
	HSS(1)	.923	.549	2.825	1	.093	2.516	.858	7.378
	ECE(1)	.583	.537	1.180	1	.277	1.792	.626	5.130
	PAR(1)	1.345	.572	5.529	1	.019	3.836	1.251	11.766
	Constant	-.737	.544	1.838	1	.175	.478		
Step 4[a]	MAC(1)	-1.220	.489	6.225	1	.013	.295	.113	.770
	HSS(1)	.922	.544	2.872	1	.090	2.513	.866	7.297
	PAR(1)	1.307	.565	5.354	1	.021	3.694	1.221	11.171
	Constant	-.624	.531	1.382	1	.240	.536		

a. Variable(s) entered on step 1: ECB, MAC, HSS, FEO, ECE, PAR.

Source: Author, 2014

These results suggest that planners, policy makers, and investors may be able to predict and make informed decisions about whether or not the choice of infrastructure, planning, and development options would be the most viable responses, based on the assessment that particular adaptation planning initiatives were primarily driven by the need for support to human and social systems and/or policy and regulations and/or perceived threats to natural resources management and conservation in relation to the risk of changing climate and related urban flooding events. For instance, a number of case studies including PlaNYC and CLIMAID (in New York City), adapting to rising tides (in San Francisco), Halifax Climate SMART, green infrastructure (burgeoning in New York City, Seattle, Chicago, and many other cities), and green roofs and many other stormwater BMPs (likewise in New York, Seattle, and Chicago) were aimed at contributing to resilience of the built environment that works to support human and social systems and reduce vulnerabilities to urban flooding risks and extreme events (Hassler and Kohler, 2014).

Model result 4: Governance and Policy (GP) options

The fourth model examined the relationships between the selected drivers of adaptation planning initiatives and the choice of governance and policy (GP) as a response option to the risk of changing climate and related flooding events in the urban context. The results of Omnibus test, Homer and Lemeshow test, and model summary are presented in Figure 4.12. The Omnibus test indicate unsatisfactory model performance (X^2 = -1.133, 1df, p = 0.287) supported by the Hosmer & Lemeshaw (H-L) test results (X^2 = 0.000, 0df, p = 0.000). The Cox & Snell R square and the Nagelkerke R square values were 0.000 suggesting that the model cannot predict choice of governance and policy (GP) as a response option.

Figure 4.12: Omnibus test, Homer and Lemeshow test, and Model summary

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	1.554	6	.956
	Block	1.554	6	.956
	Model	1.554	6	.956
Step 2[a]	Step	.000	1	.997
	Block	1.554	5	.907
	Model	1.554	5	.907
Step 3[a]	Step	-.011	1	.917
	Block	1.543	4	.819
	Model	1.543	4	.819
Step 4[a]	Step	-.096	1	.757
	Block	1.447	3	.695
	Model	1.447	3	.695
Step 5[a]	Step	-.122	1	.727
	Block	1.325	2	.516
	Model	1.325	2	.516
Step 6[a]	Step	-.192	1	.661
	Block	1.133	1	.287
	Model	1.133	1	.287
Step 7[a]	Step	-1.133	1	.287

a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	8.428	8	.393
2	5.817	7	.561
3	3.026	7	.883
4	1.036	5	.960
5	.600	2	.741
6	.000	0	.
7	.000	0	.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	128.375[a]	.016	.022
2	128.375[a]	.016	.022
3	128.386[a]	.016	.022
4	128.481[a]	.015	.020
5	128.603[a]	.014	.019
6	128.796[a]	.012	.016
7	129.928[b]	.000	.000

a. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.

b. Estimation terminated at iteration number 2 because parameter estimates changed by less than .001.

Source: Author, 2014.

The results in Table 4.8 indicate that none of the primary factors driving adaptation planning initiatives was significantly related to the choice of governance and policy options. This may imply that the primary factors driving cities to engage in particular adaptation planning initiatives had no influence on the selection of governance and policy options in relation to risks of changing climate and urban flooding events. These results may seem inconsistent with adaptation literature (e.g. Carmin et al. 2009; Djordjevic et al. 2011; Urwin and Jordan, 2008) that suggest policy and governance decisions may be taken by planners and policy makers, based on the assessment of primary factors (such as perceived threats management and conservation of urban natural resources, support to human and social systems, and economic benefits) driving particular adaptation planning initiatives in relation to risks of changing climate (e.g. sea-level rise) and urban flooding events.

Table 4.8: Variables in the equation (governance and policy options)

Variables in the Equation									
								95% C.I.for EXP(B)	
		B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Step 1[a]	ECB(1)	.048	.463	.011	1	.917	1.049	.423	2.600
	MAC(1)	-.184	.455	.164	1	.686	.832	.341	2.031
	HSS(1)	-.151	.471	.103	1	.748	.860	.341	2.165
	FEO(1)	-.507	.495	1.048	1	.306	.603	.228	1.589
	ECE(1)	-.173	.506	.117	1	.733	.841	.312	2.268
	PAR(1)	-.002	.541	.000	1	.997	.998	.346	2.880
	Constant	.251	.502	.251	1	.616	1.286		
Step 2[a]	ECB(1)	.048	.456	.011	1	.917	1.049	.429	2.563
	MAC(1)	-.184	.449	.169	1	.681	.832	.345	2.006
	HSS(1)	-.151	.471	.103	1	.748	.860	.341	2.165
	FEO(1)	-.506	.490	1.067	1	.302	.603	.231	1.575
	ECE(1)	-.173	.506	.117	1	.733	.841	.312	2.266
	Constant	.251	.498	.254	1	.614	1.286		
Step 3[a]	MAC(1)	-.175	.441	.158	1	.691	.839	.354	1.991
	HSS(1)	-.144	.466	.096	1	.757	.866	.347	2.160
	FEO(1)	-.500	.486	1.058	1	.304	.607	.234	1.573
	ECE(1)	-.169	.505	.113	1	.737	.844	.314	2.270
	Constant	.255	.497	.262	1	.609	1.290		
Step 4[a]	MAC(1)	-.183	.440	.173	1	.677	.833	.352	1.972
	FEO(1)	-.504	.486	1.079	1	.299	.604	.233	1.564
	ECE(1)	-.175	.504	.121	1	.728	.839	.313	2.252
	Constant	.158	.386	.167	1	.682	1.171		
Step 5[a]	MAC(1)	-.192	.439	.192	1	.661	.825	.349	1.949
	FEO(1)	-.510	.485	1.105	1	.293	.600	.232	1.554
	Constant	.126	.375	.114	1	.736	1.135		
Step 6[a]	FEO(1)	-.511	.485	1.111	1	.292	.600	.232	1.551
	Constant	.000	.239	.000	1	1.000	1.000		
Step 7[a]	Constant	-.128	.207	.382	1	.536	.880		

a. Variable(s) entered on step 1: ECB, MAC, HSS, FEO, ECE, PAR.

Source: Author, 2014

4.7 Implications of model results

The binary regression model results revealed significant relationships between the four primary factors driving adaptation planning initiatives and the choice of three specific adaptation options related to the risk of changing climate (e.g. sea-level rise) and flooding events in the urban context, which partially supports the hypothesis of the current study. These results may have significant theoretical and practical implications on planning practice, policy making and investment decision making with regard to climate adaptation actions in cities.

Theoretically, the model results presented may improve our understanding behind the relationships between the choice of specific adaptation options and the primary factors driving cities to engage in adaptation planning across spatial scales. The realities climate adaptation planning practices, policy and investment decision making across geo-spatial scales require better understanding of the primary factors driving the choices of specific adaptation options, which may improve the development, assessment, and selection of well-informed and viable adaptation options across spatial scales (Carmin et al. 2009; Wise et al. 2014). Further, knowing the significant relationships can guide initial reflection on the quality of adaptation plans; the timing of implementation (short term or long term), and decisions about the specific places where viable adaptation options might be implemented (Preston et al. 2010). From the policy and investment decision making perspectives, well-informed selection of adaptation options may further reduce the level of uncertainty related to their prioritization and the selection of appropriate adaptation approaches and strategies regarding implementation of effective adaptation actions (Carmin et al. 2009; Heinrichs et al. 2013; Preston et al. 2010).

Overall, the four model results suggest that planners, policy, and investment decision makers in cities may be able to predict and make well informed decisions with some level of certainty about whether or not the choice of specific adaptation options would be the most viable, based on the assessment of the primary factors driving particular adaptation planning initiatives related to the risk of changing climate, including sea-level rise and urban flooding events across a range of spatial scales and regions.

Chapter 5 - Discussion, conclusions, and further research

5.1 Discussion

This section provides discussion of the findings from case studies reviewed in relation to the guiding question of this research. First, the section provides a summary discussion on the sample distribution of cases across the United States and Canada. Second, the primary factors driving adaptation planning initiatives and the emerging adaptation response options are discussed. Third, this section focuses on the evidence of relationships between primary factors driving adaptation planning initiatives and the selection of adaptation options across scales in the urban context. Finally, the limitations emerging from the study are discussed.

5.1.1 Sample distribution of adaptation planning initiatives across U.S. and Canada

Adaptation planning initiatives related to flooding risks and extreme events in the urban context have continued to grow in time and space. The results of this study show a remarkable increase of adaptation planning cases initiated and reported between 2007 and 2010, a fact that can be attributed to the release of IPCC AR4 report (IPCC, 2007) which reinforced the need for adaptation due to the realities of changing climate and potential effects of increasing frequency and magnitude of extreme events (e.g. sea-level rise and flooding risks) on cities across a range of regions. The fact that initiatives and reports decreased between 2011 and 2012 and only began to increase slightly in 2013 may be attributed to project timescales and their need for evaluation, however, this would need to be confirmed by further analysis.

From the spatial perspective, cities across regions in the U.S. and Canada have designed and developed plans that provide adaptation response options, including strategies and measures for implementation. A majority of the plans in the U.S. are concentrated in the Northeast (e.g. New York, Massachusetts, Maine, and New Hampshire), Southwest (e.g. California), Midwest and Great Lakes (e.g. Illinois, and Michigan), and Southeast (Florida) regions, and are being supported by scientific (expert) and local knowledge, published data, climate and socioecological models, IPCC data and reports, agency and non-governmental organization (NGO) reports, peer-reviewed literature, and management plans at varying scales.

The government seems to be the main financing entity for the adaptation planning initiatives, suggesting very limited private sector investment (and perhaps a lack of private sector interest in adaptation planning due to uncertainty related to federal policies), or possibly indicating that there is a reluctance to share results for one or more reasons (Bierbaum et al. 2012; Biesbroek et al. 2010). Per the review of studies in this dissertation, most adaptation planning initiatives were concentrated in five key sectors (largely government-supported) that included transportation infrastructure (58 percent), conservation and restoration (57 percent), socio-economic development (43 percent), land use planning (41 percent), and water resources planning and management (33 percent).

5.1.2 Primary factors driving adaptation planning initiatives related to risks of changing climate and urban flooding events

In this study the author examined how specific primary driving factors of adaptation planning initiatives are associated with the selection of emerging adaptation response options across spatial scales in the urban context. The primary question formulated to guide the study was: What are the relationships between the primary factors driving adaptation planning initiatives and the selection of the specific adaptation options related to the risk of changing climate and urban flooding events across spatial scales?

The coupled DPSIR–SES framework was applied in this study to structure and organize information regarding driving factors of adaptation planning initiatives and the emerging adaptation options across a range of spatial scales in the urban context (Rounsevell et al. 2010). A systematic review methodology was used to draw knowledge from case studies on the primary factors driving urban adaptation planning initiatives and the emerging adaptation options related to risks of flooding events across various regions in the United States and Canada (e.g. Brooks et al. 2013; Berrang-Ford et al. 2011; Ford et al. 2011; Munroe et al. 2013).

The present study results suggest that a majority of adaptation planning initiatives were primarily driven by either single or multiple factors across a range of regions and spatial scales. Notably a majority of adaptation planning initiatives were driven by the need to protect and support human and social systems (56 percent), perceived threats to management and conservation of urban natural resources (51 percent), and anticipation of economic benefits (27 percent). A smaller proportion of cases were driven by perceived funding and other economic opportunities (20 percent); evidence of climate change effects (17 percent); and improvement of policy and regulations (16 percent). Adaptation planning initiatives driven by access to new information and knowledge were negligible. Nevertheless, 34 percent of initiatives were driven by general concerns about the urban environments.

These findings support recent studies in the U.S. and other developing countries in the global south that found adaptation planning initiatives to be primarily driven by incentives, information or knowledge, and resources (Carmin et al. 2009). In the same vein, Carmin et al. (2012a) argue that exogenous factors (including policy regulations and diffusion of information) are dominant motivation for adaptation planning in the long term, while endogenous factors such as local leadership or investors in addition to incentives, ideas or information and capacity are significant in the short term.

Incentives in the case of adaptation planning may include perception of risks (to human and social systems, the quality of natural resources management and conservation), anticipation of economic benefits, perceived funding and investment opportunities, and policy and regulations. According to Carmin et al. (2009), perceived risks to people, property, transportation infrastructure, and general development of cities or urban communities may incentivize adaptation planning initiatives across a range of spatial scales. For instance, perceived risks of sea-level rise, extreme flooding events and disasters (as exemplified by hurricanes Katrina, Rita, and Sandy as well as other devastating hurricanes and superstorms) in coastal cities (e.g. New York City) have been attributed to climatic change, contributing to the decision by a number of cities in North America to engage in climate action planning (Bierbaum et al. 2012).

Empirical support from the present study shows that 56 percent of urban adaptation planning cases reviewed were driven by the need to support human and social systems from the impacts of existing or future climate risks and related extreme flooding events. Likewise, perceived threats to the service provisioning urban natural resources (e.g. water and parks), their management and conservation drove 51 percent of planning cases in cities across U.S. and Canada (Lehmann et al. 2012). Notable case studies included PlaNYC and CLIMAID (in New York City), adapting to rising tides (in San Francisco), Halifax Climate SMART, green infrastructure (burgeoning in New York City, Seattle, Chicago, and many other cities), and green roofs and many other stormwater BMPs (likewise in New York, Seattle, and Chicago).

As per Carmin et al. (2009), adaptation planning initiatives that present potential multiple benefits such as green infrastructure planning (New York City, Seattle, Chicago, and many other cities) were more likely to be embraced, perhaps because the socio-economic benefits are more likely to be shared amongst a wider range of people in the community, sectors and regions.

Funding and other investment opportunities can directly or indirectly support adaptation planning initiatives (20 percent of cases in the current review) either as an incentive or resource for engaging in urban adaptation planning process (Carmin et al. 2009). For example, both domestic and international funding have been used to directly support adaptation planning processes as well as indirectly when a financial incentive contains provisions linked to adaptation-related initiatives, particularly in infrastructure, planning, and development cases (Carmin et al. 2009). In addition, adaptation financing can stimulate untapped investment opportunities that may come with developing new markets for climate-friendly technologies (e.g. participation in the carbon sequestration and abatement activities) in urban environments.

A number of studies have also found that policies at global, national and regional scales may inspire local policies and regulations related to adaptation, hence influencing adaptation planning initiatives aimed at improving existing policies and regulations (Anguelovski and Carmin, 2011; Biesbroek et al. 2010; Urwin and Jordan, 2008). For instance, policies and regulations may be improved to provide new frameworks, impose new requirements (e.g. energy efficient building) and use the threat of sanctions to foster compliance or incentives to generate interest among organizations or individuals (Carmin et al. 2009; Carmin et al. 2012). Empirical support from the present study indicate 16 percent of cases reviewed were driven by policy and regulations across spatial scales.

Although the influence of access to new information and knowledge on adaptation planning initiatives was insignificant (3 percent) in the present study, 17 percent of cases reviewed were driven by the emerging evidence of climate change effects across scales. A number of previous studies also found local experiences and scientific knowledge of the potential impacts of climate change to be influential drivers of adaptation planning in cities around the world (see Anguelovski and Carmin, 2011; Carmin et al. 2009; Heinrichs et al. 2013).

Thus, cities that considered climate change issues and adaptation as more important, and those with more information and knowledge about the benefits of adaptation, were more likely to engage in adaptation planning initiatives (Carmin et al. 2012a). Growing awareness and recognition of climate change seemed itself to have catalyzed many local adaptation planning efforts since 2007 after the launch of IPCC AR4 report (Heinrichs et al. 2013; IPCC, 2007).

General concerns emerged as a significant driving factor influencing 34 percent of urban adaptation planning initiatives in the present study. These concerns may be characterized by the growing interest in climate variability and frequency of extreme events (e.g. flooding) issues and the need to build long term resilience of urban communities focusing on either “no-regrets” or “low regrets” actions that provide multiple benefits and are good to do for reasons beyond climate adaptation—for example to reduce air and water pollution and to create more livable cities (Poyar and Beller-Simms, 2010).

5.1.3 The selection of emerging adaptation response options across spatial scales

Cities across regions in the U.S. and Canada have designed and developed plans that provide single or multiple adaptation response options and their implementation (Preston et al. 2010). Evidence from the case study review reported on in this dissertation show that majority of adaptation planning initiatives selected enhancing adaptive capacity, while approximately half of the cases opted for a combination of governance and policy, supporting effective natural resource management and conservation, and improving urban infrastructure, planning, and development.

The findings associated with this and prior research support the view that most cities would opt for ‘soft’ or low-risk options such as enhancing adaptive capacity rather than ‘hard’ action-oriented options such as infrastructure, planning, and development that will likely require major capital expenditures and structural changes, as reported by Preston et al. (2010). Another argument is that there seems to be high demand for enhancing adaptive capacity as compared to improving urban infrastructure, planning, and development due to limited investment capabilities of most cities across U.S. and Canada (Preston et al. 2010). Similar to the findings by Wise et al. (2014) the case studies reviewed in this dissertation suggests that local scale factors significantly influenced the selection of specific adaptation options.

5.1.4 Relationships between primary factors driving adaptation planning initiatives and the selection of adaptation options across spatial scales in the urban context.

This study performed bivariate and multivariate analyses to explore the significant associations and relationships between the primary factors driving urban adaptation planning initiatives and the choice of adaptation response options related to the risk of changing and urban flooding events across spatial scales.

The findings of bivariate analysis indicated evidence of "very weak" (Cramer's V= 0.170) to "moderate" association (Cramer's V= 0.245) between the four primary driving factors of adaptation planning initiatives (anticipation of economic benefits; perceived threats to management and conservation of urban natural resources; support of human and social systems; and improvement of policy and regulations) and three emerging adaptation options (enhancing adaptive capacity; supporting effective natural resource management and conservation; and improving urban infrastructure, planning, and development) at five (5) percent ($p = 0.05$) or ten (10) percent ($p = 0.1$) significance levels. These findings support the hypothesis that there was evidence of association between primary factors driving adaptation planning initiatives and the selection of adaptation response options across spatial scales. Similarly, the findings were consistent with the IPCC AR4 synthesis report that many adaptation actions (or responses) have multiple drivers embedded within broader local to regional initiatives such as water resources and land use planning (IPCC, 2007; Kelble et al. 2013).

The findings of binary logistic regression models summarized in Table 5.1 revealed significant relationships between four primary factors driving adaptation planning initiatives (namely, anticipation of economic benefits; perceived threats to management and conservation of urban natural resources; support of human and social systems; and improvement of policy and regulations) and the selection of specific adaptation options (namely enhancing adaptive capacity; management and conservation; and improving urban infrastructure, planning, and development). The following paragraphs summarize the specific findings on the significant relationships between the selected primary factors driving adaptation planning initiatives and specific adaptation response options related to the risk of changing climate and urban flooding events across scales.

Table 5.1: Summary of significant relationships between primary factors driving urban adaptation initiatives and selection of adaptation options across spatial scales

Adaptation options	**Primary factors driving urban adaptation planning initiatives**							
	NIK	ECB	HSS	MAC	PAR	FEC	ECE	GEN
AC				+	-			
MC		+	-	+				
IPD			+	-	+			
GP								

Source: Author, 2014

First, the model findings suggest that increasing anticipation of economic benefits may increase the likelihood of selecting management and conservation options in adaptation planning initiatives related to the risk of changing climate and urban flooding events. These findings seem consistent with evidence from recent adaptation studies that demonstrate the value of investing in urban green infrastructure solutions (e.g. Foster et al. 2011) in tandem with efforts to safeguard urban economies and support human and social systems (Carmin et al. 2009; Tompkins and Adger, 2004) amid uncertainties of future sea-level rise and more frequent and pronounced urban flood events. For instance, the cities of Ann Arbor and Grand Rapids, Michigan (http://grcity.us/enterprise-services/officeofenergyandsustainability/Pages/default.aspx/), Wilmington, North Carolina, and Olympia, Washington (to name just four cities), have demonstrated the need for integrating future sea-level rise and/or flood-risk projections in their planning and decision-making to ensure that the economic, environmental, and social strategies embraced are appropriate for today as well as the future. In a similar vein, the San Francisco Bay, California project "Adapting to Rising Tides" (http://www.cakex.org/case-studies/case-studies/case-studies/2737) is driven by the concerns about the potential impacts of sea-level rise on ecosystems, the economy, and infrastructure leading to the engagement of local communities in vulnerability assessments and implementation of relevant adaptation options.

Second, the model findings suggest that increasing perception of risks to management and conservation of urban natural resources (in or nearby urban landscapes) as the primary concerns of cities engaged in adaptation planning initiatives, may increase the likelihood of selecting options that seek to enhance adaptive capacity of urban communities and/or management and conservation options, while discouraging cities from selecting infrastructure, planning, and development options. These findings seem consistent with a number of studies (e.g. Armitage, 2005; Liao, 2012; Plummer et al. 2013; Tompkins and Adger, 2004) which argue that enhancing adaptive capacity is necessary for effective performance of urban natural resources (e.g. watersheds) in sustaining provision of ecosystem services (e.g. water quality and quantity).

As noted below, a number of recent case studies have demonstrated that management and conservation options (e.g. urban stormwater management and green infrastructure interventions) can contribute greatly to resilience of urban natural resources (Armitage, 2005; Kirshen et al. 2008). Examples of adaptation initiatives in the U.S. that have engaged management and conservation options include the following communities: Keene, New Hampshire; New York City, New York; Seattle (King County), Washington; and Chicago, Illinois. Each of these communities have developed climate adaptation strategies and are in the process of implementing adaptation measures such as ecologically based (natural or green) infrastructure that is predominantly decentralized and integrated with natural functions and settings (as in Keene), green infrastructure (burgeoning in New York City, Seattle, Chicago, and many other cities), and green roofs, rain-gardens, bio-swales, and many other stormwater BMPs (likewise in New York, Seattle, Chicago, etc.) as per Bierbaum et al. (2012).

Notably, the green infrastructure interventions (such as urban ecosystem restoration, naturalized stormwater management, green roofs, urban forestry, and urban agriculture) in the City of Chicago (http://www.chicagoclimateaction.org/pages/adaptation/11.php) and New York City (http://www.nyc.gov/html/dep/html/stormwater/nyc_green_infrastructure_plan.shtml) have demonstrated potential to provide long-term multiple benefits (e.g. reduced energy consumption, decreased stormwater runoff, water capture and conservation, storm-surge protection, and defense against lake- or sea-level rise) critical for combating the impacts of urban flood events, creating healthy built environments, and improving quality of life of the urban communities (Armitage, 2005; Kirshen et al. 2008; Wilby and Keenan, 2012). The greening of combined sewer infrastructure in the City of Philadelphia has enabled protection of streams and rivers, reduced greenhouse gas emissions and flooding impacts, improved air quality, and enhanced adaptation to a changing climate (http://www.phillywatersheds.org/ltcpu/).

Third, the model findings suggest that increased need to support humans and social systems (that includes people, property and transportation infrastructure amongst others) in cities through adaptation planning initiatives, may increase the likelihood of selecting infrastructure, planning, and development options, while discouraging the selection of management and conservation options. These findings seems consistent with the findings of Carmin, et al. (2009) that indicate managing the potential impacts of sea-level rise may include improvement or redevelopment of infrastructure, in addition to development restriction and relocation of residents to accommodate the risk of urban flooding events. For instance, many emerging green and gray infrastructure planning and development cases (such as PlaNYC in New York City) are aimed at contributing to resilience of the built environment that works to support human and social systems and reduce vulnerabilities to urban flooding risks and extreme events (Hassler and Kohler, 2014). They seek to do this by involving communities in ecologically based (natural or green) infrastructure initiatives such as green roofs, rain-gardens, bio-swales, and many other stormwater BMPs (Bierbaum et al. 2012).

Fourth, the model findings suggest that increasing policy and regulations as the primary concerns of adaptation planning initiatives in cities may increase the likelihood of selecting infrastructure, planning, and development options, while reducing the likelihood of selecting options that seek to enhance adaptive capacity. These findings seem to be at least partially consistent with recent studies (e.g. Djordjevic et al. 2011; Urwin and Jordan, 2008) and the outcomes of adaptation planning case studies such as PlaNYC, New York City (http://www.nyc.gov/html/dep/html/stormwater/nyc_green_infrastructure_plan.shtml) and the City of Keene, New Hampshire (http://www.ci.keene.nh.us/sites/default/files/CMPprint-final-1027-fullversion_2.pdf). These studies suggest that policy-driven adaptation planning initiatives are likely to consider investments in critical urban infrastructure and land use planning and regulations that restrict developments in floodplains and at-risk coastal sites across geo-political scales in the long term, while in the short-term prefer climate risk awareness and early-warning-system options in addition to other strategies that enhance adaptive capacity.

5.1.5 Limitations of the study

Because climate adaptation planning research is relatively new, there is limited peer-reviewed literature on adaptation cases or evaluation of adaptation planning process and outcomes (Bierbaum et al. 2012; Biesbroek et al. 2013; Carmin et al. 2012a; Rounsevell et al, 2010). Much of the documentation that does exist is in "grey" (non-peer-reviewed) literature, such as government reports and planning documents, agency "white" or background papers, and "expressions of interest" reports officially submitted as part of the U.S National Climate Assessment report (Bierbaum et al. 2012).

Although designed to be as comprehensive and transparent as possible, the systematic review methodology described in this dissertation has a number of limitations that need to be considered. The quality of the systematic review is mainly dependent on the quality and quantity of information and case study data that is available to the reviewer (Garg et al. 2008). Because much of the data associated with adaptation planning cases exists in "grey" (non-peer-reviewed) literature it is not readily accessible. Further research, including targeted inquiries, specific information and document requests, phone and e-mail interviews and conversations, and even visits to local communities could deepen the understanding of specific cases. In the future, in-depth case studies could be completed by interested researchers.

The methodological limitations included the search strategy, the synthesis methods, and the quality and reliability assessments. This study adapted search strategies from authors in other fields such as medical, environmental conservation, and ecology and developed a search strategy in consultation with major advisor and PhD committee. Also, the search strategy relied on cases reported in databases (e.g. Climate Adaptation Knowledge Exchange), specialist search, and previous surveys/reports. Therefore, any errors in the data sources during extraction might have been transferred resulting to errors in the extraction and data analysis in the present study.

The North America-wide regional approach that was used in the search strategy may have caused limitations in capturing primary factors driving adaptation planning initiatives and the emerging adaptation response options across different urban scales. Combining numerous studies across North America could have resulted in sampling errors arising from omission of cases and publication bias (Garg et al. 2008). The limitations of publication bias could have arisen from the differences in study designs, methods, and conflict of interest among others. In this dissertation, publication and reporting bias may have been minimized by using online databases (e.g. Climate Adaptation Knowledge Exchange) that had undergone rigorous quality assessment and reporting process.

Also, a regional approach was very challenging as the researcher had to face major human resources and timeframe constraints, and required readily available data sets as well. Hence, the cases included in the analysis were certainly not exhaustive given limited available information. There are likely a number of recently initiated and completed studies not captured by this research effort.

Finally, it is important to note that conducting the systematic review individually, as in this study, resulted in a number of limitations. Typically bias, especially in the search and selection of individual case studies, are rectified by engaging a second reviewer so that any differences in selections of cases are discussed and agreed upon. However, for this dissertation research, there was lack of a second reviewer and the author conducted a two stage review spaced between two months to reduce bias. A test-retest reliability assessment was conducted to determine the level of agreement and consistency of decision regarding selection (inclusion/exclusion) of individual case studies. Conducting the study individually in a limited amount of time may have led to some level of author bias/conflict of interest that resulted in some studies either not being included in the review or mistakenly included.

5.2 Conclusions

This dissertation provided a detailed overview of the status and drivers of adaptation planning initiatives, planning support systems, emerging adaptation options, and barriers to implementation adaptation planning actions across the globe—with a particular focus on North America (e.g. Brooks et al. 2013; Berrang-Ford et al. 2011; Ford et al. 2011; Munroe et al. 2013). In order to address the gap between plan-making and the implementation of adaptation actions there was need to: (1) understand the primary factors driving urban adaptation planning initiatives and the emerging adaptation options across scales, and (2) explore the relationships between primary factors driving adaptation planning initiatives and the choice of adaptation options related to flooding risks and related extreme events across scales in the urban context.

The present study used the modified DPSIR-SES framework and the systematic review approach to synthesize evidence from urban adaptation planning case studies with respect to the primary questions of this study in order to generate objective and generalizable findings across the U.S and Canada. The findings revealed a rapid growth in urban adaptation planning initiatives focusing on the risks of changing climate (e.g. sea-level rise) and flooding events across spatial scales. Most of the adaptation planning initiatives were primarily driven by either single or multiple factors that included perception of risks to the management and conservation of urban natural resources, need for support to humans and social systems, and anticipation of economic benefits related to the existing or potential impacts of changing climate and flooding events. Other factors driving cities in North America to engage in adaptation planning initiatives included, funding and investment opportunities, evidence of climate change effects, improvement of policy and regulations, and general concerns.

These findings support previous studies by Anguelovski and Carmin (2011), Carmin et al. (2009) and Carmin et al. (2012a) that incentives, information, and resources (capacity) tend to motivate cities to engage in adaptation planning initiatives. However, access to new information and knowledge seemed to play a limited role as a driving factor for adaptation planning initiatives in the present study, which is contrary to the findings of previous studies (such as Carmin et al. 2009; Carmin et al. 2012a; Heinrichs et al. 2013) that linked improved information access and knowledge to engagement in adaptation planning.

The main focus of the present study was to better understand the relationships between primary factors driving adaptation planning initiatives and the selection of the specific adaptation options related to the risk of changing climate and urban flooding events across spatial scales. The findings of binary logistic regression models suggest that the choice of specific adaptation options (namely enhancing adaptive capacity; management and conservation; and improving urban infrastructure, planning, and development) may be influenced by single or multiple primary factors driving adaptation planning initiatives (namely, anticipation of economic benefits; perceived threats to management and conservation of urban natural resources; support of human and social systems; and improvement of policy and regulations) in relation to the risk of changing climate, including sea-level rise and urban flooding events. These findings do not imply that other primary factors (namely access to information and knowledge; perceived funding and economic opportunities; evidence of climate change effects; and general concerns) have no relationships with the selection of adaptation options, only that the review did not find evidence to support such claims. A good example is the Urban Boston case study (http://www.cakex.org/case-studies/5312) primarily driven by perceived funding and other economic opportunities and general concerns to perceived risks of urban communities to coastal flooding opted for enhancing adaptive capacity of urban communities to effectively respond the perceived risks of coastal flooding by increasing access to resources that: (1) promote adaptive capacity; (2) raise awareness of flood risks and potential adaptation options; (3) integrate existing knowledge and values in adaptation planning process; and (4) engage local communities in promoting collective community and/or regional partnering in adaptation actions (Gregg, 2010; Kirshen et al. 2008).

These findings may have significant implications in bridging various planning-implementation gaps. For instance, planners and policy decision makers may begin to predict whether or not the choice of specific adaptation response options may be the most viable based on the assessment primary factors driving of adaptation planning initiatives, which may eliminate the trial-and-error approach to the design and development of quality adaptation plans, namely by well-informed choices in regards to robust adaptation options and by setting the stage for developing achievable implementation strategies and policies for effective adaptation actions (Preston et al. 2010). With this knowledge the city administrators, urban planners and policy decision makers in the U.S. and Canada may begin to re-evaluate their existing urban adaptation plans and make necessary adjustments where possible to improve their implementation and effectiveness across spatial scales.

Flexible and robust adaptation options may greatly help in overcoming uncertainties to the implementation of adaptation actions, especially in resource-scarce regions where adaptation plans are weak or absent (Bierbaum et al. 2012; Plummer and Armitage, 2010). A good example are cities in Africa and Asia where climate adaptation plans are being developed fairly rapidly, with little evidence of adaptation actions being implemented to reduce the impacts of changing climate and related extreme events (Carmin et al. 2012a; Carmin et al. 2009). The experiences of Carmin et al. (2012a) in Durban revealed the absence of planning guidelines and frameworks for monitoring and evaluating successes or failures of adaptation planning initiatives. Thus, the findings of the present study may offer support for the planning process (development, assessment, and selection of options) and future development of a framework for monitoring and evaluation of implemented adaptation actions to improve their effectiveness and success across a range of scales and regions (Preston et al. 2010; Tompkins et al. 2010). In addition, the findings may facilitate strategic development, replication, and mainstreaming of best practices and/or innovative actions by planners and policy decision makers in cities like Dar es Salaam, Tanzania; and Nairobi, Kenya; amongst others that have limited resources for adaptation planning.

Nevertheless, this dissertation provides a foundation for development of planning and decision support tools that could be used for assessment of adaptation plans and implementation of robust adaptation options (as per IPCC, 2007). Better assessment of adaptation plans may overcome uncertainties and generate some consensus around best practices for cities already engaged or seeking to engage in adaptation planning initiatives and improve implementation of adaptation actions across a range of scales and regions (Carmin et al. 2009; Bierbaum et al. 2012; Preston et al. 2010).

5.3 Further research directions

By examining the adaptation literature and assessing case examples of urban adaptation planning in the region, it becomes apparent that key knowledge gaps exist. Future research addressing the knowledge gaps may seek to undertake a synthesis of climate adaptation interventions currently being designed and implemented, building on adaptation planning initiatives already identified in this review to explore the extent to which these interventions have considered the linkages between what is driving the initiatives and the selection of adaptation options. Researchers considering to conduct systematic reviews in their synthesis of climate adaptation planning interventions may need to devote more time in the developing search strategies, especially for relevant grey literature and methods for data analysis (Garg et al. 2008). For instance, in using logistic regression analyses researchers may consider applying the Rasch model to create scales that build variations among the factor variables to generate improved results.

Finally, decision support tools that could be used for assessment of adaptation plans and implementation of specific adaptation options, need to be further developed and tested for applicability with a view to addressing the following important questions:

- What are the successes and failures of the adaptation planning initiatives across different scales? What successes and failures are most common?
- What determines success or failure of the adaptation planning initiatives? Do the associations or relationships between primary driving factors of the adaptation planning initiatives and the emerging adaptation options influence the success or failure of specific types of implementation actions? If so, why? If not, why not?
- What differences exist in regards to successes or failures of adaptation planning in different nation states? How can nations in Africa and other countries with emerging economies and planning infrastructure constraints (particularly in regards to limitations related to technical aspects and personnel needs) most effectively approach the climate adaptation planning process?

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Appendix A - Selected adaptation planning cases in U.S and Canada

PID	Project Name	References
1	A Climate Change Action Plan for the Florida Reef Tract (2010-2015)	Score, A. (2010)
2	A Framework for Climate Change Adaptation in Hawaii	Kershner, J. (2010)
3	A Roadmap for Action_ The Chicago Climate Action Plan	Gregg, R. M. and Hitt, J. L. (2012)
4	Adaptation Behavior on the Front Line of Climate Change and Accelerating Sea-level rise in the Florida Keys	Score, A. (2010)
5	Adaptation to Climate Change Impacts on the Coastal Wetlands in the Gulf of Mexico	Score, A. (2010)
6	Adaptation to Sea-level rise in Florida	Noss, R. (2010)
7	Adapting to Rising Tides in San Francisco Bay, California	Gregg, R.M. and Polgar, S. (2010)
8	Adapting to Sea-level rise in Hayward, California	Kershner, J. (2010)
9	Alabama’s Baldwin County Grasses in Classes Program	Gregg, R. M. (2010)
10	Albemarle-Pamlico National Estuary Program's Climate Ready Estuaries Project	Gregg, R. M. (2010)
11	Assessing Impacts and Developing Adaptation Strategies for Connecticut’s Natural and Built Environments	Gregg, R. M. (2010)
12	Assessing the Risk of 100-year Freshwater Floods in the Lamprey River Watershed of New Hampshire Resulting from Climate Change and Land Use	Gregg, R. M. (2010)
13	Atlantic Canada Climate Change Adaptation Strategy	Hitt, J. (2010)
14	Atlantic Climate Adaptation Solutions (ACASA)	Hitt, J. (2010)
15	Barnegat Bay Climate Change Adaptation Strategy Development	Gregg, R. M. (2010)
16	Bay Area Ecosystems Climate Change Consortium	Gregg, R. M. (2010)
17	British Columbia's Local Climate Change Visioning Project	Gregg, R. M. (2010)
18	Broward County Climate Change Task Force and Climate Change Initiatives	Score, A. (2010)
19	Building Capacity for Climate-Resilient Communities and Water Conservation in the Huron River Watershed	Gregg, R. M. (2012)
20	Building Climate Resiliency in the Lower Willamette Region of Western Oregon	Kershner, J. and Adams, S. (2011)
21	California Department of Water Resources Adaptation Strategy	Feifel, K. (2010)
22	California Energy Commission's Climate Change Research Program	Score, A. (2011)
23	City of New Castle, Delaware Coastal Resiliency Action Plan	Gregg, R. M. (2010)
24	ClimAID_ Developing a Climate Change Impacts and Adaptation Assessment for New York State	Gregg, R. M. (2012)
25	Climate Adaptation in the City of Ann Arbor, Michigan	Kershner, J. M. (2012)
26	Climate Change Adaptation Guidelines for Sea Dikes and Coastal Flood Hazard Land Use in British Columbia	Neale, T. (2011)
27	Climate Change Adaptation in Kimberley, British Columbia	Gregg, R. M. (2010)
28	Climate Change Adaptation Planning at the State Level in Minnesota	Gregg, R. M. and Hitt, J. L. (2012)

29	Climate Change Adaptation Planning at the State Level in Pennsylvania	Gregg, R. M. (2012)
30	Climate Change Adaptation Planning in Fresno County, California	Koopman, M. and Meis, K. (2012)
31	Climate Change Adaptation Planning in San Luis Obispo County	Kershner, J. (2010)
32	Climate Change Adaptation Planning in the City of Chula Vista, California	Kershner, J. (2010).
33	Climate Change Adaptations for Land Use Planners	Kershner, J. (2010)
34	Climate Change and the Florida Keys	Score, A. (2010)
35	Climate Change Mitigation and Adaptation Planning in Wisconsin's Lake Michigan Coastal Communities	Gregg, R. M. (2012)
36	Climate Change Vulnerability Assessment for Long Island Sound via Sentinel Monitoring	Gregg, R. M. (2010)
37	Climate Change, Coastal Flooding, and Environmental Justice in Urban Boston Communities	Gregg, R.M. (2010)
38	Coastal Adaptation Plan for the Town of Groton, Connecticut	Gregg, R.M. (2010)
39	Coastal Resilience: Visualizing Climate Change Impacts and Coastal Hazards and Implementing Solutions in Long Island Sound	Gregg, R.M. (2010)
40	Creating a Gulf Coast Community Handbook for Restoration and Adaptation	Gregg, R.M. (2010)
41	Creating a More Resilient Yellowknife_ Climate Change Impacts and Municipal Decision Making	Hitt, J. (2010)
42	Creating a National Adaptation Strategy for the United States_ The Interagency Climate Change Adaptation Task Force	Gregg, R. M. (2010)
43	Dawson Community Climate Change Adaptation Plan	Feifel, K. (2010)
44	Delaware Sea-level rise Adaptation Initiative	Gregg, R. M. (2010)
45	Developing a Washington State Climate Change Impacts Response Strategy	Gregg, R. M. (2010)
46	Developing Ontario's Climate Change Adaptation Strategy and Action Plan	Gregg, R. M. (2012)
47	Documenting Traditional Ecological Knowledge in Northwest Alaska	Feifel, K. (2010)
48	Florida Planning Toolbox_ Climate Change Tools	Score, A. (2010)
49	Fostering a Climate-Informed Community Perspective in the Great Lakes_ The Great Lakes Community Climate Program	Hitt, J. L. and Gregg, R. M. (2012)
50	Great Lakes Adaptation Assessment for Cities	Gregg, R. M. (2012)
51	Greater Vancouver's Stormwater Management Program	Feifel, K. (2010)
52	Halifax Climate SMART_ The Climate Sustainable Mitigation and Adaptation Risk Toolkit	Hitt, J. (2010)
53	Homer, Alaska Climate Action Plan	Feifel, K. (2010)
54	Identifying Opportunities for Climate Adaptation in the Delaware Estuary	Gregg, R. M. (2010)
55	Implementation of Maryland's Climate Action Plan	Feifel, K. (2010)
56	Incorporating Climate Change Impacts into Activities in Charlotte Harbor, Florida	Gregg, R. M. (2010)
57	Incorporating Climate Change into the Casco Bay Estuary Partnership	Gregg, R. M. (2009)
58	Increasing Coastal Resilience through Restoration and Education in Narragansett Bay, Rhode Island	Gregg, R. M. (2010)
59	Indian River Lagoon and City of Satellite Beach, Florida Adaptation Project	Gregg, R. M. (2010)
60	Integrating Climate Change Adaptation Strategies into Maryland's Coastal Land Conservation Targeting	Feifel, K. and Papiez, C. (2010)
61	Integrating Climate Change into the U.S. National Estuarine Research Reserve System	Gregg, R. M. (2010)

62	Investigating the Impact of Climate Change on Combined and Separate Sewer Overflows in Milwaukee Watersheds	Gregg, R. M. (2012)
63	Lake Tahoe Climate Change Adaptation Strategy Project	Score, A. (2011)
64	London, Ontario's Climate Change Adaptation Strategy	Feifel, K. M. (2012)
65	Malibu Land Use and Local Implementation Plans_ Setbacks and Sea-level rise	Hitt, J. (2010)
66	Managed Retreat at Surfer's Point, California	Feifel, K. (2010)
67	Maryland's Coast-Smart Communities Initiative	Hitt, J. (2010)
68	Municipal Adaptations to Create Resilient Beach Communities in Southern Maine: The Coastal Hazard Resiliency Tools Project	Gregg, R. M. (2010)
69	New Jersey Climate Change Adaptation Using Community Plan Endorsements	Feifel, K. (2010)
70	North Bay Climate Adaptation Initiative	Feifel, K. (2010)
71	Oyster River Watershed Culvert Study	Gregg, R. M. (2010)
72	Planning for Climate Change in the Province of Quebec	Gregg, R. M. (2012)
73	Planning for Climate Change_ A Workshop for San Francisco Bay Area Planners	Gregg, R. M. (2010)
74	Planning for Sea-level rise and Storm Surge in Worcester County, Maryland	Hitt, J. (2010)
75	Planning for Sea-level rise in Olympia, Washington	Feifel, K. (2010)
76	Planning for the Impacts of Sea-level rise and Climate Change in North Carolina	Kershner, J. (2010)
77	PlaNYC_ A Comprehensive Sustainability Plan for New York City	Feifel, K. (2010)
78	Preparing for a Changing Climate in Missoula County and Western Montana	Alban, J. and Rasker, R. (2012)
79	Preparing for Climate Change and Sea-level rise in New Brunswick	Kershner, J. (2010)
80	Preparing for Climate Change in California's East Bay Municipal Utility District	Gregg, R. M. (2010)
81	Preparing for Climate Change in the Great Lakes Region	Feifel, K. (2010)
82	Preparing for Climate Change in the Upper Willamette River Basin	Kershner, J. (2010)
83	Preparing for Sea-level rise on Graham Island, British Columbia	Kershner, J. (2010)
84	Preparing for the Changing Climate_ a Northeast-Focused Needs Assessment	Stephenson, R. (2011)
85	Preparing for the Impacts of Sea-level rise on the California Coast	Kershner, J. (2010)
86	Project Clean Lake: Updating Cleveland's Sewer Systems to Reduce Stormwater Overflows	Feifel, K. M. (2012)
87	Québec City's Environmental Services Adaptation Plan	Feifel, K. M. (2012)
88	Rein in the Runoff: Michigan's Spring Lake Stormwater Management Project	Feifel, K. M. (2012)
89	Restoration and Managed Retreat of Pacifica State Beach	Kershner, J. (2010)
90	Sacramento County, California Climate Change Action Plan	Score, A. (2011)
91	Salt Marsh Vulnerability Assessment and Adaptation Plan Development in San Francisco Bay, California	Gregg, R. M. (2010)
92	San Francisco Bay Conservation and Development Commission's Climate Change Planning Program	Feifel, K. (2010)
93	Scenic Hudson Land Trust: Prioritizing Lands in Light of Sea-level rise	Feifel, K. (2010)
94	Sea-level rise Adaptation Report for the City of Wilmington, North Carolina	Feifel, K. (2010)
95	Sea-level rise Guidance for Somerset County, Maryland	Hitt, J. (2010)
96	Sea-level rise in the Gulf of Mexico_ Awareness and Action Tools for the Climate Outreach Community of Practice	Gregg, R. M. (2010)
97	South Bay Salt Pond Restoration Project	Kershner, J. (2010)

98	Southeast Florida Regional Climate Change Compact	Adams, S. and Gregg, R. M. (2010)
99	Survey Says. . . Great Lakes Coastal Communities Choose Climate Adaptation!	Kahl, K. and Stirratt, H. (2012)
100	Sustainable Development Initiatives in the Polar Town of Iqaluit, Canada	Feifel, K. (2010)
101	The City of Toronto's Climate Change Adaptation Strategy: From Development to Implementation	Feifel, K. M. (2012)
102	The Climate Change Response Framework: Supporting Climate-Smart Conservation and Forest Management in the Great Lakes Region	Kershner, J. M. (2012)
103	The Michigan Climate Coalition: Enhancing Networking and Collaboration, Communication, and Action Around Climate Change in Michigan	Kershner, J. M. (2012)
104	The National StormSmart Coasts Network_ Linking Coastal Decision Makers to Resources	Gregg, R. M. (2010)
105	The Oregon Climate Change Adaptation Framework	Kershner, J. (2010)
106	The San Diego Foundation's Climate Initiative Program	Feifel, K. (2010)
107	The Sonoran Desert Conservation Plan_ A Landscape-scale Conservation Initiative in Pima County, Arizona	Powell, B. and R.M. Gregg (2010)
108	U.S. Environmental Protection Agency's Climate Ready Estuaries Program	Gregg, R. M. (2010)
109	Understanding and Modeling the Impacts of Human Behavior and Climate Change on the Maumee River Watershed, Ohio	Kershner, J. M. (2012)
110	Updating the Illinois Wildlife Action Plan_ Using a Climate Change Vulnerability Assessment to Inform Conservation Priorities	Kahl, K. et al. (2011)
111	Using Ecosystem-Based Management as an Adaptation Strategy in the Pacific Fishery Management Council	Gregg, R. M. (2010)
112	Using Green Infrastructure to Prevent Sewage Overflows in Detroit	Kershner, J. M. (2012)
113	Using Outreach to Catalyze Small Changes in Climate Change Adaptation on Bald Head Island, North Carolina	Feifel, K. and Gregg, R. M. (2010)
114	Using Robust Decision-making as a Tool for Water Resources Planning in Southern California	Feifel, K. (2010)
115	Vulnerability of King County, Washington Wastewater Treatment Facilities to Sea-level rise	Feifel, K. (2010)
116	Vulnerable Mediterranean Climate Coastal Habitats in Bahía de San Quintín, Baja California, México	Score, A. (2010)
117	Water Utility Climate Alliance	Feifel, K. and Gregg, R. M. (2010)
118	Weather–Extreme Trends (WET): The Minnehaha Creek Watershed Stormwater Adaptation Study	Hitt, J. L. (2012)
119	What Could Changing Great Lakes Water Levels Mean for our Coastal Communities?	Kahl, K. and Stirratt, H. (2012)
120	Whitehorse Community Climate Change Adaptation Plan	Feifel, K. and Gregg, R.M. (2011)
121	Wisconsin Initiative on Climate Change Impacts: A Bottom-Up Approach to Developing Climate Change Adaptation Strategies	Gregg, R. M. (2012)

Appendix B - Documents review checklist

	Documents review checklist				
	Background information				
Q1	Document title				
	Document type (e.g. survey report/ published research etc)				
Q2	Year published				
Q3	Author/ affiliation				
Q4	Name of Region/State/City				
	Adaptation project information				
Q5	Project location	Y/N	Q10	**Driving factors motivating adaptation planning**	**Y/N**
	a) Neighborhood			a) Access to new information or knowledge	
	b) City			b) Perceived threats to economic benefits	
	c) State			c) Perceived threats to conservation & management	
	d) National			d) Perceived threats to human or social systems	
	e) Regional			e) Perceived funding & other economic opportunities	
Q6	Boundary/Jurisdiction (Spatial scale)			f) Evidence of climate change effects	
	a) Local/Community			g) Policy and regulation concerns	
	b) City			h) General concerns	
	c) State		Q11	**Adaptation response options/measures/strategies**	
	d) National			a) Enhancing adaptive capacity	
	e) Regional			b) Management & Conservation	
Q7	Sociopolitical setting			c) Infrastructure planning & development	
	a) Urban			d) Governance & Policy	
	b) Suburban		Q12	Information sources for vulnerability assessment & adaptation planning	
	c) Rural			a) Review, books, handbooks	
	d) Industrial			b) Literature (peer-reviewed)	
Q8	Sector addressed			c) Reports (Agency/NGO)	
	a) Development (Socioeconomic)			d) Reports (Unpublished)	
	b) Conservation/ Restoration			e) Management plans	
	c) Transportation/ Infrastructure			f) Published data	
	d) Water resources			g) Models [Climate/Sociecological/Ecosystem]	
	e) Land use planning			h) IPCC	
	f) Public health			i) Scientific Expert Knowledge	
	g) Education/ Research			j) Other Local Knowledge	
	h) Policy		Q13	Project evaluation status	
	i) Other			a) Monitoring in place	
Q9	Funding sources			b) Metrics identified	
	a) Government			c) Not planned	
	b) Foundation			d) Funding expired	
	c) Government/ Foundation			e) N/S	
	d) Government/ Private donation		Q14	Project time frame (years)	
	e) Foundation/ Private donation			a) 1-3	
	f) Government/ Foundation/ Private donation			b) 3-5	
	g) Business/ Government			c) 5-10	
	h) Business/ Foundation/ Government/ Private donation			d) 10+	
	i) CICEET			e) Ongoing	
	j) N/S			f) N/S	

Appendix C - Variable coding labels

Code	Variable label
NIK	Access to new information & knowledge
ECB	Anticipation of economic benefits
MAC	Perceived threats to resource management & conservation
HSS	Support to human or social systems
FEO	Perceived funding & other economic opportunities
ECE	Evidence of climate change effects
GEN	General concerns
PAR	Policy & regulations
AC	Enhancing adaptive capacity
MC	Natural resources management & conservation
IPD	Infrastructure planning & development
GP	Governance & policy

Appendix D - Binary data for analysis

PID	NIK	ECB	MAC	HSS	FEO	ECE	PAR	GEN	AC	MC	IPD	GP
1	0	1	0	0	1	0	0	0	1	1	0	1
2	1	1	1	1	0	0	1	1	1	1	0	1
3	0	0	0	0	0	0	1	0	1	1	1	1
4	0	1	1	1	0	1	0	0	1	0	0	0
5	0	0	1	0	0	1	0	0	1	1	0	1
6	0	0	1	1	0	1	0	0	1	1	1	1
7	0	0	1	1	0	0	0	1	1	0	0	0
8	0	0	0	1	0	0	0	0	1	0	1	0
9	0	0	0	0	0	0	0	1	1	0	0	0
10	0	0	1	1	0	0	0	1	1	0	0	0
11	0	0	1	1	1	0	1	1	1	0	0	0
12	0	0	0	0	0	1	0	1	1	1	1	0
13	0	0	1	1	1	1	0	1	1	1	0	1
14	0	1	1	0	1	1	0	1	1	1	0	0
15	0	1	1	1	1	0	0	0	1	1	0	1
16	0	0	0	0	0	0	0	0	1	0	0	1
17	0	0	1	1	0	0	0	1	1	0	0	0
18	0	1	0	1	0	0	0	0	0	1	0	1
19	NS	NS	NS	NS	NS	NS	NS	NS	1	1	1	1
20	0	1	1	1	0	1	0	1	1	1	0	0
21	0	1	1	1	0	0	1	0	1	1	1	0
22	NS	NS	NS	NS	NS	NS	NS	NS	0	1	0	0
23	0	0	0	1	0	0	0	0	1	0	0	1
24	NS	NS	NS	NS	NS	NS	NS	NS	1	0	0	1
25	NS	NS	NS	NS	NS	NS	NS	NS	1	0	1	1
26	0	0	0	1	0	1	0	0	0	0	1	1
27	0	1	0	1	1	0	0	1	1	0	0	0
28	NS	NS	NS	NS	NS	NS	NS	NS	1	1	1	1
29	NS	NS	NS	NS	NS	NS	NS	NS	1	0	0	1
30	0	0	1	1	0	0	0	0	1	0	0	0
31	0	1	0	1	1	0	0	0	1	1	1	0
32	0	0	0	0	0	0	0	1	1	1	1	0
33	0	1	0	1	1	0	0	1	1	1	1	1
34	0	1	1	0	0	0	0	1	1	0	0	0
35	0	0	0	1	0	0	0	0	1	0	1	0

36	0	0	1	0	1	0	1	0	0	1	0	0
37	0	0	0	0	0	1	0	1	1	0	0	0
38	0	0	1	0	1	0	0	0	1	0	0	1
39	0	1	1	0	0	0	0	1	1	0	0	1
40	0	0	1	0	1	0	0	0	1	1	0	0
41	0	0	0	1	1	1	0	0	1	0	0	0
42	0	1	1	1	0	0	1	0	1	0	0	1
43	0	0	0	1	0	0	0	0	1	0	0	1
44	0	0	1	1	0	0	0	0	1	0	0	1
45	0	0	1	1	0	0	1	1	1	0	0	1
46	NS	NS	NS	NS	NS	NS	NS	NS	1	0	0	1
47	0	0	1	1	0	0	0	0	1	1	0	0
48	0	1	0	1	1	1	0	1	1	0	1	0
49	NS	NS	NS	NS	NS	NS	NS	NS	1	0	0	0
50	NS	NS	NS	NS	NS	NS	NS	NS	1	0	1	1
51	0	0	1	1	0	0	0	0	1	0	1	1
52	0	1	0	1	0	0	0	1	1	1	0	1
53	0	1	1	1	0	0	1	1	1	1	1	1
54	0	0	1	1	0	1	0	0	1	0	0	1
55	0	1	1	1	0	1	1	0	1	0	1	0
56	0	1	1	1	1	0	0	0	1	1	0	1
57	0	1	1	1	1	0	0	0	1	1	0	0
58	0	0	1	0	0	0	0	1	0	1	0	0
59	0	0	1	1	1	0	0	0	1	0	0	1
60	0	0	1	0	0	0	1	0	1	1	1	1
61	0	0	1	1	0	0	0	1	1	1	0	0
62	NS	NS	NS	NS	NS	NS	NS	NS	1	0	1	1
63	0	0	1	1	0	1	1	0	1	1	1	1
64	NS	NS	NS	NS	NS	NS	NS	NS	1	0	1	1
65	0	1	1	1	0	0	1	0	0	1	1	0
66	0	0	0	0	0	0	0	1	0	1	1	0
67	0	1	1	1	0	1	1	1	1	0	1	0
68	0	1	1	0	0	0	0	0	1	0	0	1
69	NS	NS	NS	NS	NS	NS	NS	NS	1	1	1	1
70	0	0	1	1	0	0	0	1	1	1	0	0
71	0	0	1	1	1	0	0	0	1	1	1	0
72	NS	NS	NS	NS	NS	NS	NS	NS	1	0	0	1
73	0	0	1	1	1	0	0	0	1	0	1	0
74	0	1	1	1	0	0	1	0	1	1	1	0
75	0	0	0	1	0	0	0	1	0	0	1	0

76	NS	NS	NS	NS	NS	NS	NS	NS	1	0	0	1
77	0	0	0	1	0	0	1	0	0	0	1	0
78	1	1	1	1	1	1	0	1	1	0	0	0
79	0	0	0	1	1	0	0	1	1	0	0	1
80	0	0	0	1	0	0	0	0	1	1	1	0
81	0	0	1	0	0	0	0	0	1	0	0	0
82	0	0	1	1	0	0	0	0	1	1	1	0
83	0	0	0	1	1	0	0	1	1	0	0	1
84	0	0	1	1	0	1	0	0	1	0	0	1
85	0	0	1	1	0	1	0	1	1	1	1	0
86	NS	NS	NS	NS	NS	NS	NS	NS	0	1	1	1
87	1	0	1	1	0	0	0	0	1	0	0	1
88	NS	NS	NS	NS	NS	NS	NS	NS	1	0	1	0
89	0	0	1	1	1	0	0	0	1	1	1	0
90	0	0	0	0	0	0	1	0	0	1	0	1
91	0	0	1	1	0	0	0	0	1	0	0	1
92	0	1	1	1	0	0	0	1	1	1	1	1
93	0	0	1	0	1	0	0	0	1	1	0	0
94	0	1	1	0	0	0	0	0	1	1	0	0
95	0	1	1	1	1	1	1	1	1	1	1	0
96	0	0	0	1	0	0	0	0	1	0	0	0
97	NS	NS	NS	NS	NS	NS	NS	NS	1	1	1	1
98	0	1	1	1	0	1	0	1	1	1	1	1
99	NS	NS	NS	NS	NS	NS	NS	NS	1	0	0	0
100	0	0	0	1	0	0	0	1	1	0	1	1
101	NS	NS	NS	NS	NS	NS	NS	NS	1	0	0	1
102	NS	NS	NS	NS	NS	NS	NS	NS	1	0	0	0
103	NS	NS	NS	NS	NS	NS	NS	NS	1	0	0	0
104	0	1	1	1	0	0	0	0	1	0	0	0
105	0	1	1	1	0	0	0	1	1	1	0	1
106	NS	NS	NS	NS	NS	NS	NS	NS	1	0	1	0
107	0	0	1	0	0	0	0	1	0	1	1	1
108	0	0	1	0	0	0	0	0	1	1	1	1
109	NS	NS	NS	NS	NS	NS	NS	NS	1	1	0	0
110	1	0	1	0	0	0	1	1	1	1	0	1
111	0	1	1	1	0	0	1	1	1	1	0	0
112	NS	NS	NS	NS	NS	NS	NS	NS	1	0	1	0
113	0	0	1	1	0	0	0	0	1	0	0	0
114	0	0	0	1	0	0	0	0	1	0	1	1
115	0	0	0	1	0	0	0	0	1	0	1	0

116	0	1	1	1	0	0	0	1	1	1	0	1
117	0	0	0	1	0	0	0	1	1	0	1	1
118	NS	NS	NS	NS	NS	NS	NS	NS	1	0	1	1
119	NS	NS	NS	NS	NS	NS	NS	NS	1	0	0	0
120	0	0	0	0	0	1	0	1	1	0	0	1
121	NS	NS	NS	NS	NS	NS	NS	NS	1	0	0	1
Notes: ‘1’ = Presence ‘0’ = Absence ‘NS’ = Not Stated												

Appendix E - Bivariate analysis – cross tabulation results

This appendix provides the SPSS output on Chi-square (X^2) statistics (Phi coefficient and Cramer's V) analyses signifying the statistical strength of association between each the independent variables (driving factors motivating adaptation planning initiatives) and the dependent variables (emerging adaptation response options) at 5 percent ($p = 0.05$) or 10 percent ($p = 0.1$) significance levels.

Crosstabs

Notes

Output Created		09-MAR-2014 18:11:59
Comments		
Input	Data	C:\Users\phil\Desktop\CS_DataAnalysis\CSAanalysis\SPSS_data\CSA1.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	121
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics for each table are based on all the cases with valid data in the specified range(s) for all variables in each table.
Syntax		CROSSTABS /TABLES=AC MC IPD GP BY NIK ECB MAC HSS FEO ECE PAR GEN /FORMAT=AVALUE TABLES /STATISTICS=CHISQ PHI LAMBDA /CELLS=COUNT ROW COLUMN TOTAL SRESID /COUNT ROUND CELL.
Resources	Processor Time	00:00:00.31
	Elapsed Time	00:00:05.65
	Dimensions Requested	2
	Cells Available	131029

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
AC * NIK	94	77.7%	27	22.3%	121	100.0%
AC * ECB	94	77.7%	27	22.3%	121	100.0%
AC * MAC	94	77.7%	27	22.3%	121	100.0%
AC * HSS	94	77.7%	27	22.3%	121	100.0%
AC * FEO	94	77.7%	27	22.3%	121	100.0%
AC * ECE	94	77.7%	27	22.3%	121	100.0%
AC * PAR	94	77.7%	27	22.3%	121	100.0%
AC * GEN	94	77.7%	27	22.3%	121	100.0%
MC * NIK	94	77.7%	27	22.3%	121	100.0%
MC * ECB	94	77.7%	27	22.3%	121	100.0%
MC * MAC	94	77.7%	27	22.3%	121	100.0%
MC * HSS	94	77.7%	27	22.3%	121	100.0%
MC * FEO	94	77.7%	27	22.3%	121	100.0%
MC * ECE	94	77.7%	27	22.3%	121	100.0%
MC * PAR	94	77.7%	27	22.3%	121	100.0%
MC * GEN	94	77.7%	27	22.3%	121	100.0%
IPD * NIK	94	77.7%	27	22.3%	121	100.0%
IPD * ECB	94	77.7%	27	22.3%	121	100.0%
IPD * MAC	94	77.7%	27	22.3%	121	100.0%
IPD * HSS	94	77.7%	27	22.3%	121	100.0%
IPD * FEO	94	77.7%	27	22.3%	121	100.0%
IPD * ECE	94	77.7%	27	22.3%	121	100.0%
IPD * PAR	94	77.7%	27	22.3%	121	100.0%
IPD * GEN	94	77.7%	27	22.3%	121	100.0%
GP * NIK	94	77.7%	27	22.3%	121	100.0%
GP * ECB	94	77.7%	27	22.3%	121	100.0%
GP * MAC	94	77.7%	27	22.3%	121	100.0%
GP * HSS	94	77.7%	27	22.3%	121	100.0%
GP * FEO	94	77.7%	27	22.3%	121	100.0%
GP * ECE	94	77.7%	27	22.3%	121	100.0%
GP * PAR	94	77.7%	27	22.3%	121	100.0%
GP * GEN	94	77.7%	27	22.3%	121	100.0%

AC * NIK

Crosstab

			NIK		Total
			Absence	Presence	
AC	Absence	Count	10	0	10
		% within AC	100.0%	0.0%	100.0%
		% within NIK	11.1%	0.0%	10.6%
		% of Total	10.6%	0.0%	10.6%
		Std. Residual	.1	-.7	
	Presence	Count	80	4	84
		% within AC	95.2%	4.8%	100.0%
		% within NIK	88.9%	100.0%	89.4%
		% of Total	85.1%	4.3%	89.4%
		Std. Residual	.0	.2	
Total		Count	90	4	94
		% within AC	95.7%	4.3%	100.0%
		% within NIK	100.0%	100.0%	100.0%
		% of Total	95.7%	4.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.497[a]	1	.481		
Continuity Correction[b]	.000	1	1.000		
Likelihood Ratio	.921	1	.337		
Fisher's Exact Test				1.000	.633
Linear-by-Linear Association	.492	1	.483		
N of Valid Cases	94				

a. 2 cells (50.0%) have expected count less than 5. The minimum expected count is .43.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		AC Dependent	.000	.000
		NIK Dependent	.000	.000
	Goodman and Kruskal tau	AC Dependent	.005	.002
		NIK Dependent	.005	.003

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		AC Dependent	.[b]	.[b]
		NIK Dependent	.[b]	.[b]
	Goodman and Kruskal tau	AC Dependent		.483[c]
		NIK Dependent		.483[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.073	.481
	Cramer's V	.073	.481
N of Valid Cases		94	

AC * ECB

Crosstab

			ECB		Total
			Absence	Presence	
AC	Absence	Count	8	2	10
		% within AC	80.0%	20.0%	100.0%
		% within ECB	13.1%	6.1%	10.6%
		% of Total	8.5%	2.1%	10.6%
		Std. Residual	.6	-.8	
	Presence	Count	53	31	84
		% within AC	63.1%	36.9%	100.0%
		% within ECB	86.9%	93.9%	89.4%
		% of Total	56.4%	33.0%	89.4%
		Std. Residual	-.2	.3	
Total		Count	61	33	94
		% within AC	64.9%	35.1%	100.0%
		% within ECB	100.0%	100.0%	100.0%
		% of Total	64.9%	35.1%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	1.121[a]	1	.290		
Continuity Correction[b]	.502	1	.479		
Likelihood Ratio	1.216	1	.270		
Fisher's Exact Test				.485	.245
Linear-by-Linear Association	1.109	1	.292		
N of Valid Cases	94				

a. 1 cells (25.0%) have expected count less than 5. The minimum expected count is 3.51.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		AC Dependent	.000	.000
		ECB Dependent	.000	.000
	Goodman and Kruskal tau	AC Dependent	.012	.019
		ECB Dependent	.012	.019

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		AC Dependent	.[b]	.[b]
		ECB Dependent	.[b]	.[b]
	Goodman and Kruskal tau	AC Dependent		.292[c]
		ECB Dependent		.292[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.109	.290
	Cramer's V	.109	.290
N of Valid Cases		94	

AC * MAC

Crosstab

			MAC		Total
			Absence	Presence	
AC	Absence	Count	6	4	10
		% within AC	60.0%	40.0%	100.0%
		% within MAC	18.8%	6.5%	10.6%
		% of Total	6.4%	4.3%	10.6%
		Std. Residual	1.4	-1.0	
	Presence	Count	26	58	84
		% within AC	31.0%	69.0%	100.0%
		% within MAC	81.3%	93.5%	89.4%
		% of Total	27.7%	61.7%	89.4%
		Std. Residual	-.5	.3	
Total		Count	32	62	94
		% within AC	34.0%	66.0%	100.0%
		% within MAC	100.0%	100.0%	100.0%
		% of Total	34.0%	66.0%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	3.358[a]	1	.067		
Continuity Correction[b]	2.189	1	.139		
Likelihood Ratio	3.163	1	.075		
Fisher's Exact Test				.084	.072
Linear-by-Linear Association	3.322	1	.068		
N of Valid Cases	94				

a. 1 cells (25.0%) have expected count less than 5. The minimum expected count is 3.40.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.048	.073
		AC Dependent	.000	.000
		MAC Dependent	.063	.096
	Goodman and Kruskal tau	AC Dependent	.036	.041
		MAC Dependent	.036	.040

Directional Measures

			Approx. T[b]	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.634	.526
		AC Dependent	.[c]	.[c]
		MAC Dependent	.634	.526
	Goodman and Kruskal tau	AC Dependent		.068[d]
		MAC Dependent		.068[d]

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Cannot be computed because the asymptotic standard error equals zero.
d. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.189	.067
	Cramer's V	.189	.067
N of Valid Cases		94	

AC * HSS

Crosstab

			HSS		Total
			Absence	Presence	
AC	Absence	Count	5	5	10
		% within AC	50.0%	50.0%	100.0%
		% within HSS	19.2%	7.4%	10.6%
		% of Total	5.3%	5.3%	10.6%
		Std. Residual	1.3	-.8	
	Presence	Count	21	63	84
		% within AC	25.0%	75.0%	100.0%
		% within HSS	80.8%	92.6%	89.4%
		% of Total	22.3%	67.0%	89.4%
		Std. Residual	-.5	.3	
Total		Count	26	68	94
		% within AC	27.7%	72.3%	100.0%
		% within HSS	100.0%	100.0%	100.0%
		% of Total	27.7%	72.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	2.791[a]	1	.095		
Continuity Correction[b]	1.682	1	.195		
Likelihood Ratio	2.530	1	.112		
Fisher's Exact Test				.133	.101
Linear-by-Linear Association	2.762	1	.097		
N of Valid Cases	94				

a. 1 cells (25.0%) have expected count less than 5. The minimum expected count is 2.77.

b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.088
		AC Dependent	.000	.000
		HSS Dependent	.000	.122
	Goodman and Kruskal tau	AC Dependent	.030	.040
		HSS Dependent	.030	.039

Directional Measures

			Approx. T[b]	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.000	1.000
		AC Dependent	.[c]	.[c]
		HSS Dependent	.000	1.000
	Goodman and Kruskal tau	AC Dependent		.097[d]
		HSS Dependent		.097[d]

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Cannot be computed because the asymptotic standard error equals zero.
d. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.172	.095
	Cramer's V	.172	.095
N of Valid Cases		94	

AC * FEO

Crosstab

			FEO		Total
			Absence	Presence	
AC	Absence	Count	9	1	10
		% within AC	90.0%	10.0%	100.0%
		% within FEO	12.9%	4.2%	10.6%
		% of Total	9.6%	1.1%	10.6%
		Std. Residual	.6	-1.0	
	Presence	Count	61	23	84
		% within AC	72.6%	27.4%	100.0%
		% within FEO	87.1%	95.8%	89.4%
		% of Total	64.9%	24.5%	89.4%
		Std. Residual	-.2	.3	
Total		Count	70	24	94
		% within AC	74.5%	25.5%	100.0%
		% within FEO	100.0%	100.0%	100.0%
		% of Total	74.5%	25.5%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	1.420[a]	1	.233		
Continuity Correction[b]	.653	1	.419		
Likelihood Ratio	1.684	1	.194		
Fisher's Exact Test				.443	.217
Linear-by-Linear Association	1.405	1	.236		
N of Valid Cases	94				

a. 1 cells (25.0%) have expected count less than 5. The minimum expected count is 2.55.

b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		AC Dependent	.000	.000
		FEO Dependent	.000	.000
	Goodman and Kruskal tau	AC Dependent	.015	.019
		FEO Dependent	.015	.018

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		AC Dependent	.[b]	.[b]
		FEO Dependent	.[b]	.[b]
	Goodman and Kruskal tau	AC Dependent		.236[c]
		FEO Dependent		.236[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.123	.233
	Cramer's V	.123	.233
N of Valid Cases		94	

AC * ECE

Crosstab

			ECE		Total
			Absence	Presence	
AC	Absence	Count	9	1	10
		% within AC	90.0%	10.0%	100.0%
		% within ECE	12.3%	4.8%	10.6%
		% of Total	9.6%	1.1%	10.6%
		Std. Residual	.4	-.8	
	Presence	Count	64	20	84
		% within AC	76.2%	23.8%	100.0%
		% within ECE	87.7%	95.2%	89.4%
		% of Total	68.1%	21.3%	89.4%
		Std. Residual	-.2	.3	
Total		Count	73	21	94
		% within AC	77.7%	22.3%	100.0%
		% within ECE	100.0%	100.0%	100.0%
		% of Total	77.7%	22.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.982[a]	1	.322		
Continuity Correction[b]	.348	1	.556		
Likelihood Ratio	1.150	1	.284		
Fisher's Exact Test				.448	.294
Linear-by-Linear Association	.972	1	.324		
N of Valid Cases	94				

a. 1 cells (25.0%) have expected count less than 5. The minimum expected count is 2.23.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		AC Dependent	.000	.000
		ECE Dependent	.000	.000
	Goodman and Kruskal tau	AC Dependent	.010	.016
		ECE Dependent	.010	.016

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		AC Dependent	.[b]	.[b]
		ECE Dependent	.[b]	.[b]
	Goodman and Kruskal tau	AC Dependent		.324[c]
		ECE Dependent		.324[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.102	.322
	Cramer's V	.102	.322
N of Valid Cases		94	

AC * PAR

Crosstab

			PAR		
			Absence	Presence	Total
AC	Absence	Count	6	4	10
		% within AC	60.0%	40.0%	100.0%
		% within PAR	8.0%	21.1%	10.6%
		% of Total	6.4%	4.3%	10.6%
		Std. Residual	-.7	1.4	
	Presence	Count	69	15	84
		% within AC	82.1%	17.9%	100.0%
		% within PAR	92.0%	78.9%	89.4%
		% of Total	73.4%	16.0%	89.4%
		Std. Residual	.2	-.5	
Total		Count	75	19	94
		% within AC	79.8%	20.2%	100.0%
		% within PAR	100.0%	100.0%	100.0%
		% of Total	79.8%	20.2%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	2.717[a]	1	.099		
Continuity Correction[b]	1.517	1	.218		
Likelihood Ratio	2.338	1	.126		
Fisher's Exact Test				.113	.113
Linear-by-Linear Association	2.688	1	.101		
N of Valid Cases	94				

a. 1 cells (25.0%) have expected count less than 5. The minimum expected count is 2.02.

b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		AC Dependent	.000	.000
		PAR Dependent	.000	.000
	Goodman and Kruskal tau	AC Dependent	.029	.042
		PAR Dependent	.029	.041

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		AC Dependent	.[b]	.[b]
		PAR Dependent	.[b]	.[b]
	Goodman and Kruskal tau	AC Dependent		.101[c]
		PAR Dependent		.101[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.170	.099
	Cramer's V	.170	.099
N of Valid Cases		94	

AC * GEN

Crosstab

			GEN		Total
			Absence	Presence	
AC	Absence	Count	6	4	10
		% within AC	60.0%	40.0%	100.0%
		% within GEN	11.3%	9.8%	10.6%
		% of Total	6.4%	4.3%	10.6%
		Std. Residual	.2	-.2	
	Presence	Count	47	37	84
		% within AC	56.0%	44.0%	100.0%
		% within GEN	88.7%	90.2%	89.4%
		% of Total	50.0%	39.4%	89.4%
		Std. Residual	-.1	.1	
Total		Count	53	41	94
		% within AC	56.4%	43.6%	100.0%
		% within GEN	100.0%	100.0%	100.0%
		% of Total	56.4%	43.6%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.060[a]	1	.807		
Continuity Correction[b]	.000	1	1.000		
Likelihood Ratio	.060	1	.807		
Fisher's Exact Test				1.000	.542
Linear-by-Linear Association	.059	1	.808		
N of Valid Cases	94				

a. 1 cells (25.0%) have expected count less than 5. The minimum expected count is 4.36.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		AC Dependent	.000	.000
		GEN Dependent	.000	.000
	Goodman and Kruskal tau	AC Dependent	.001	.005
		GEN Dependent	.001	.005

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		AC Dependent	.[b]	.[b]
		GEN Dependent	.[b]	.[b]
	Goodman and Kruskal tau	AC Dependent		.808[c]
		GEN Dependent		.808[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.025	.807
	Cramer's V	.025	.807
N of Valid Cases		94	

MC * NIK

Crosstab

			NIK		Total
			Absence	Presence	
MC	Absence	Count	45	2	47
		% within MC	95.7%	4.3%	100.0%
		% within NIK	50.0%	50.0%	50.0%
		% of Total	47.9%	2.1%	50.0%
		Std. Residual	.0	.0	
	Presence	Count	45	2	47
		% within MC	95.7%	4.3%	100.0%
		% within NIK	50.0%	50.0%	50.0%
		% of Total	47.9%	2.1%	50.0%
		Std. Residual	.0	.0	
Total		Count	90	4	94
		% within MC	95.7%	4.3%	100.0%
		% within NIK	100.0%	100.0%	100.0%
		% of Total	95.7%	4.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.000[a]	1	1.000		
Continuity Correction[b]	.000	1	1.000		
Likelihood Ratio	.000	1	1.000		
Fisher's Exact Test				1.000	.692
Linear-by-Linear Association	.000	1	1.000		
N of Valid Cases	94				

a. 2 cells (50.0%) have expected count less than 5. The minimum expected count is 2.00.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		MC Dependent	.000	.000
		NIK Dependent	.000	.000
	Goodman and Kruskal tau	MC Dependent	.000	.000
		NIK Dependent	.000	.000

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		MC Dependent	.[b]	.[b]
		NIK Dependent	.[b]	.[b]
	Goodman and Kruskal tau	MC Dependent		1.000[c]
		NIK Dependent		1.000[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.000	1.000
	Cramer's V	.000	1.000
N of Valid Cases		94	

MC * ECB

Crosstab

			ECB		
			Absence	Presence	Total
MC	Absence	Count	36	11	47
		% within MC	76.6%	23.4%	100.0%
		% within ECB	59.0%	33.3%	50.0%
		% of Total	38.3%	11.7%	50.0%
		Std. Residual	1.0	-1.4	
	Presence	Count	25	22	47
		% within MC	53.2%	46.8%	100.0%
		% within ECB	41.0%	66.7%	50.0%
		% of Total	26.6%	23.4%	50.0%
		Std. Residual	-1.0	1.4	
Total		Count	61	33	94
		% within MC	64.9%	35.1%	100.0%
		% within ECB	100.0%	100.0%	100.0%
		% of Total	64.9%	35.1%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	5.650[a]	1	.017		
Continuity Correction[b]	4.670	1	.031		
Likelihood Ratio	5.732	1	.017		
Fisher's Exact Test				.030	.015
Linear-by-Linear Association	5.590	1	.018		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 16.50.

b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.138	.064
		MC Dependent	.234	.107
		ECB Dependent	.000	.000
	Goodman and Kruskal tau	MC Dependent	.060	.048
		ECB Dependent	.060	.049

Directional Measures

			Approx. T[b]	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	1.953	.051
		MC Dependent	1.953	.051
		ECB Dependent	.[c]	.[c]
	Goodman and Kruskal tau	MC Dependent		.018[d]
		ECB Dependent		.018[d]

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Cannot be computed because the asymptotic standard error equals zero.
d. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.245	.017
	Cramer's V	.245	.017
N of Valid Cases		94	

MC * MAC

Crosstab

			MAC		Total
			Absence	Presence	
MC	Absence	Count	21	26	47
		% within MC	44.7%	55.3%	100.0%
		% within MAC	65.6%	41.9%	50.0%
		% of Total	22.3%	27.7%	50.0%
		Std. Residual	1.3	-.9	
	Presence	Count	11	36	47
		% within MC	23.4%	76.6%	100.0%
		% within MAC	34.4%	58.1%	50.0%
		% of Total	11.7%	38.3%	50.0%
		Std. Residual	-1.3	.9	
Total		Count	32	62	94
		% within MC	34.0%	66.0%	100.0%
		% within MAC	100.0%	100.0%	100.0%
		% of Total	34.0%	66.0%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	4.738[a]	1	.030		
Continuity Correction[b]	3.838	1	.050		
Likelihood Ratio	4.798	1	.028		
Fisher's Exact Test				.049	.025
Linear-by-Linear Association	4.688	1	.030		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 16.00.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.127	.093
		MC Dependent	.213	.149
		MAC Dependent	.000	.000
	Goodman and Kruskal tau	MC Dependent	.050	.045
		MAC Dependent	.050	.045

Directional Measures

			Approx. T[b]	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	1.281	.200
		MC Dependent	1.281	.200
		MAC Dependent	.[c]	.[c]
	Goodman and Kruskal tau	MC Dependent		.030[d]
		MAC Dependent		.030[d]

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Cannot be computed because the asymptotic standard error equals zero.
d. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.225	.030
	Cramer's V	.225	.030
N of Valid Cases		94	

MC * HSS

Crosstab

			HSS		Total
			Absence	Presence	
MC	Absence	Count	9	38	47
		% within MC	19.1%	80.9%	100.0%
		% within HSS	34.6%	55.9%	50.0%
		% of Total	9.6%	40.4%	50.0%
		Std. Residual	-1.1	.7	
	Presence	Count	17	30	47
		% within MC	36.2%	63.8%	100.0%
		% within HSS	65.4%	44.1%	50.0%
		% of Total	18.1%	31.9%	50.0%
		Std. Residual	1.1	-.7	
Total		Count	26	68	94
		% within MC	27.7%	72.3%	100.0%
		% within HSS	100.0%	100.0%	100.0%
		% of Total	27.7%	72.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	3.403[a]	1	.065		
Continuity Correction[b]	2.605	1	.107		
Likelihood Ratio	3.445	1	.063		
Fisher's Exact Test				.106	.053
Linear-by-Linear Association	3.367	1	.067		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 13.00.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.110	.064
		MC Dependent	.170	.099
		HSS Dependent	.000	.000
	Goodman and Kruskal tau	MC Dependent	.036	.038
		HSS Dependent	.036	.038

Directional Measures

			Approx. T[b]	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	1.590	.112
		MC Dependent	1.590	.112
		HSS Dependent	.[c]	.[c]
	Goodman and Kruskal tau	MC Dependent		.067[d]
		HSS Dependent		.067[d]

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Cannot be computed because the asymptotic standard error equals zero.
d. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.190	.065
	Cramer's V	.190	.065
N of Valid Cases		94	

MC * FEO

Crosstab

			FEO		Total
			Absence	Presence	
MC	Absence	Count	37	10	47
		% within MC	78.7%	21.3%	100.0%
		% within FEO	52.9%	41.7%	50.0%
		% of Total	39.4%	10.6%	50.0%
		Std. Residual	.3	-.6	
	Presence	Count	33	14	47
		% within MC	70.2%	29.8%	100.0%
		% within FEO	47.1%	58.3%	50.0%
		% of Total	35.1%	14.9%	50.0%
		Std. Residual	-.3	.6	
Total		Count	70	24	94
		% within MC	74.5%	25.5%	100.0%
		% within FEO	100.0%	100.0%	100.0%
		% of Total	74.5%	25.5%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.895[a]	1	.344		
Continuity Correction[b]	.504	1	.478		
Likelihood Ratio	.898	1	.343		
Fisher's Exact Test				.478	.239
Linear-by-Linear Association	.886	1	.347		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 12.00.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.056	.066
		MC Dependent	.085	.100
		FEO Dependent	.000	.000
	Goodman and Kruskal tau	MC Dependent	.010	.020
		FEO Dependent	.010	.020

Directional Measures

			Approx. T[b]	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.819	.413
		MC Dependent	.819	.413
		FEO Dependent	.[c]	.[c]
	Goodman and Kruskal tau	MC Dependent		.347[d]
		FEO Dependent		.347[d]

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Cannot be computed because the asymptotic standard error equals zero.
d. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.098	.344
	Cramer's V	.098	.344
N of Valid Cases		94	

MC * ECE

Crosstab

			ECE		Total
			Absence	Presence	
MC	Absence	Count	36	11	47
		% within MC	76.6%	23.4%	100.0%
		% within ECE	49.3%	52.4%	50.0%
		% of Total	38.3%	11.7%	50.0%
		Std. Residual	-.1	.2	
	Presence	Count	37	10	47
		% within MC	78.7%	21.3%	100.0%
		% within ECE	50.7%	47.6%	50.0%
		% of Total	39.4%	10.6%	50.0%
		Std. Residual	.1	-.2	
Total		Count	73	21	94
		% within MC	77.7%	22.3%	100.0%
		% within ECE	100.0%	100.0%	100.0%
		% of Total	77.7%	22.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.061[a]	1	.804		
Continuity Correction[b]	.000	1	1.000		
Likelihood Ratio	.061	1	.804		
Fisher's Exact Test				1.000	.500
Linear-by-Linear Association	.061	1	.805		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 10.50.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.015	.125
		MC Dependent	.021	.180
		ECE Dependent	.000	.000
	Goodman and Kruskal tau	MC Dependent	.001	.005
		ECE Dependent	.001	.005

Directional Measures

			Approx. T[b]	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.117	.907
		MC Dependent	.117	.907
		ECE Dependent	.[c]	.[c]
	Goodman and Kruskal tau	MC Dependent		.805[d]
		ECE Dependent		.805[d]

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Cannot be computed because the asymptotic standard error equals zero.
d. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.026	.804
	Cramer's V	.026	.804
N of Valid Cases		94	

MC * PAR

Crosstab

			PAR		Total
			Absence	Presence	
MC	Absence	Count	41	6	47
		% within MC	87.2%	12.8%	100.0%
		% within PAR	54.7%	31.6%	50.0%
		% of Total	43.6%	6.4%	50.0%
		Std. Residual	.6	-1.1	
	Presence	Count	34	13	47
		% within MC	72.3%	27.7%	100.0%
		% within PAR	45.3%	68.4%	50.0%
		% of Total	36.2%	13.8%	50.0%
		Std. Residual	-.6	1.1	
Total		Count	75	19	94
		% within MC	79.8%	20.2%	100.0%
		% within PAR	100.0%	100.0%	100.0%
		% of Total	79.8%	20.2%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	3.232[a]	1	.072		
Continuity Correction[b]	2.375	1	.123		
Likelihood Ratio	3.295	1	.069		
Fisher's Exact Test				.122	.061
Linear-by-Linear Association	3.198	1	.074		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.50.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.106	.060
		MC Dependent	.149	.086
		PAR Dependent	.000	.000
	Goodman and Kruskal tau	MC Dependent	.034	.036
		PAR Dependent	.034	.036

Directional Measures

			Approx. T[b]	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	1.628	.103
		MC Dependent	1.628	.103
		PAR Dependent	.[c]	.[c]
	Goodman and Kruskal tau	MC Dependent		.074[d]
		PAR Dependent		.074[d]

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Cannot be computed because the asymptotic standard error equals zero.
d. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.185	.072
	Cramer's V	.185	.072
N of Valid Cases		94	

MC * GEN

Crosstab

			GEN		Total
			Absence	Presence	
MC	Absence	Count	28	19	47
		% within MC	59.6%	40.4%	100.0%
		% within GEN	52.8%	46.3%	50.0%
		% of Total	29.8%	20.2%	50.0%
		Std. Residual	.3	-.3	
	Presence	Count	25	22	47
		% within MC	53.2%	46.8%	100.0%
		% within GEN	47.2%	53.7%	50.0%
		% of Total	26.6%	23.4%	50.0%
		Std. Residual	-.3	.3	
Total		Count	53	41	94
		% within MC	56.4%	43.6%	100.0%
		% within GEN	100.0%	100.0%	100.0%
		% of Total	56.4%	43.6%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.389[a]	1	.533		
Continuity Correction[b]	.173	1	.677		
Likelihood Ratio	.390	1	.533		
Fisher's Exact Test				.678	.339
Linear-by-Linear Association	.385	1	.535		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 20.50.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.034	.071
		MC Dependent	.064	.132
		GEN Dependent	.000	.000
	Goodman and Kruskal tau	MC Dependent	.004	.013
		GEN Dependent	.004	.013

Directional Measures

			Approx. T[b]	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.469	.639
		MC Dependent	.469	.639
		GEN Dependent	.[c]	.[c]
	Goodman and Kruskal tau	MC Dependent		.535[d]
		GEN Dependent		.535[d]

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Cannot be computed because the asymptotic standard error equals zero.
d. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.064	.533
	Cramer's V	.064	.533
N of Valid Cases		94	

IPD * NIK

Crosstab

			NIK		Total
			Absence	Presence	
IPD	Absence	Count	53	4	57
		% within IPD	93.0%	7.0%	100.0%
		% within NIK	58.9%	100.0%	60.6%
		% of Total	56.4%	4.3%	60.6%
		Std. Residual	-.2	1.0	
	Presence	Count	37	0	37
		% within IPD	100.0%	0.0%	100.0%
		% within NIK	41.1%	0.0%	39.4%
		% of Total	39.4%	0.0%	39.4%
		Std. Residual	.3	-1.3	
Total		Count	90	4	94
		% within IPD	95.7%	4.3%	100.0%
		% within NIK	100.0%	100.0%	100.0%
		% of Total	95.7%	4.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	2.712[a]	1	.100		
Continuity Correction[b]	1.263	1	.261		
Likelihood Ratio	4.117	1	.042		
Fisher's Exact Test				.151	.130
Linear-by-Linear Association	2.683	1	.101		
N of Valid Cases	94				

a. 2 cells (50.0%) have expected count less than 5. The minimum expected count is 1.57.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		IPD Dependent	.000	.000
		NIK Dependent	.000	.000
	Goodman and Kruskal tau	IPD Dependent	.029	.006
		NIK Dependent	.029	.015

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		IPD Dependent	.[b]	.[b]
		NIK Dependent	.[b]	.[b]
	Goodman and Kruskal tau	IPD Dependent		.101[c]
		NIK Dependent		.101[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.170	.100
	Cramer's V	.170	.100
N of Valid Cases		94	

IPD * ECB

Crosstab

			ECB		Total
			Absence	Presence	
IPD	Absence	Count	36	21	57
		% within IPD	63.2%	36.8%	100.0%
		% within ECB	59.0%	63.6%	60.6%
		% of Total	38.3%	22.3%	60.6%
		Std. Residual	-.2	.2	
	Presence	Count	25	12	37
		% within IPD	67.6%	32.4%	100.0%
		% within ECB	41.0%	36.4%	39.4%
		% of Total	26.6%	12.8%	39.4%
		Std. Residual	.2	-.3	
Total		Count	61	33	94
		% within IPD	64.9%	35.1%	100.0%
		% within ECB	100.0%	100.0%	100.0%
		% of Total	64.9%	35.1%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.192[a]	1	.662		
Continuity Correction[b]	.047	1	.829		
Likelihood Ratio	.192	1	.661		
Fisher's Exact Test				.825	.416
Linear-by-Linear Association	.189	1	.663		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 12.99.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		IPD Dependent	.000	.000
		ECB Dependent	.000	.000
	Goodman and Kruskal tau	IPD Dependent	.002	.009
		ECB Dependent	.002	.009

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		IPD Dependent	.[b]	.[b]
		ECB Dependent	.[b]	.[b]
	Goodman and Kruskal tau	IPD Dependent		.663[c]
		ECB Dependent		.663[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.045	.662
	Cramer's V	.045	.662
N of Valid Cases		94	

IPD * MAC

Crosstab

			MAC		Total
			Absence	Presence	
IPD	Absence	Count	15	42	57
		% within IPD	26.3%	73.7%	100.0%
		% within MAC	46.9%	67.7%	60.6%
		% of Total	16.0%	44.7%	60.6%
		Std. Residual	-1.0	.7	
	Presence	Count	17	20	37
		% within IPD	45.9%	54.1%	100.0%
		% within MAC	53.1%	32.3%	39.4%
		% of Total	18.1%	21.3%	39.4%
		Std. Residual	1.2	-.9	
Total		Count	32	62	94
		% within IPD	34.0%	66.0%	100.0%
		% within MAC	100.0%	100.0%	100.0%
		% of Total	34.0%	66.0%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	3.850[a]	1	.050		
Continuity Correction[b]	3.026	1	.082		
Likelihood Ratio	3.816	1	.051		
Fisher's Exact Test				.074	.041
Linear-by-Linear Association	3.809	1	.051		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 12.60.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.029	.081
		IPD Dependent	.054	.149
		MAC Dependent	.000	.000
	Goodman and Kruskal tau	IPD Dependent	.041	.042
		MAC Dependent	.041	.042

Directional Measures

			Approx. T[b]	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.354	.723
		IPD Dependent	.354	.723
		MAC Dependent	.[c]	.[c]
	Goodman and Kruskal tau	IPD Dependent		.051[d]
		MAC Dependent		.051[d]

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Cannot be computed because the asymptotic standard error equals zero.
d. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.202	.050
	Cramer's V	.202	.050
N of Valid Cases		94	

IPD * HSS

Crosstab

			HSS		Total
			Absence	Presence	
IPD	Absence	Count	19	38	57
		% within IPD	33.3%	66.7%	100.0%
		% within HSS	73.1%	55.9%	60.6%
		% of Total	20.2%	40.4%	60.6%
		Std. Residual	.8	-.5	
	Presence	Count	7	30	37
		% within IPD	18.9%	81.1%	100.0%
		% within HSS	26.9%	44.1%	39.4%
		% of Total	7.4%	31.9%	39.4%
		Std. Residual	-1.0	.6	
Total		Count	26	68	94
		% within IPD	27.7%	72.3%	100.0%
		% within HSS	100.0%	100.0%	100.0%
		% of Total	27.7%	72.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	2.330[a]	1	.127		
Continuity Correction[b]	1.665	1	.197		
Likelihood Ratio	2.409	1	.121		
Fisher's Exact Test				.160	.097
Linear-by-Linear Association	2.305	1	.129		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 10.23.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		IPD Dependent	.000	.000
		HSS Dependent	.000	.000
	Goodman and Kruskal tau	IPD Dependent	.025	.030
		HSS Dependent	.025	.030

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		IPD Dependent	.[b]	.[b]
		HSS Dependent	.[b]	.[b]
	Goodman and Kruskal tau	IPD Dependent		.129[c]
		HSS Dependent		.129[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.157	.127
	Cramer's V	.157	.127
N of Valid Cases		94	

IPD * FEO

Crosstab

			FEO		Total
			Absence	Presence	
IPD	Absence	Count	40	17	57
		% within IPD	70.2%	29.8%	100.0%
		% within FEO	57.1%	70.8%	60.6%
		% of Total	42.6%	18.1%	60.6%
		Std. Residual	-.4	.6	
	Presence	Count	30	7	37
		% within IPD	81.1%	18.9%	100.0%
		% within FEO	42.9%	29.2%	39.4%
		% of Total	31.9%	7.4%	39.4%
		Std. Residual	.5	-.8	
Total		Count	70	24	94
		% within IPD	74.5%	25.5%	100.0%
		% within FEO	100.0%	100.0%	100.0%
		% of Total	74.5%	25.5%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	1.403[a]	1	.236		
Continuity Correction[b]	.888	1	.346		
Likelihood Ratio	1.442	1	.230		
Fisher's Exact Test				.333	.173
Linear-by-Linear Association	1.389	1	.239		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.45.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		IPD Dependent	.000	.000
		FEO Dependent	.000	.000
	Goodman and Kruskal tau	IPD Dependent	.015	.024
		FEO Dependent	.015	.024

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		IPD Dependent	.[b]	.[b]
		FEO Dependent	.[b]	.[b]
	Goodman and Kruskal tau	IPD Dependent		.239[c]
		FEO Dependent		.239[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.122	.236
	Cramer's V	.122	.236
N of Valid Cases		94	

IPD * ECE

Crosstab

			ECE		Total
			Absence	Presence	
IPD	Absence	Count	46	11	57
		% within IPD	80.7%	19.3%	100.0%
		% within ECE	63.0%	52.4%	60.6%
		% of Total	48.9%	11.7%	60.6%
		Std. Residual	.3	-.5	
	Presence	Count	27	10	37
		% within IPD	73.0%	27.0%	100.0%
		% within ECE	37.0%	47.6%	39.4%
		% of Total	28.7%	10.6%	39.4%
		Std. Residual	-.3	.6	
Total		Count	73	21	94
		% within IPD	77.7%	22.3%	100.0%
		% within ECE	100.0%	100.0%	100.0%
		% of Total	77.7%	22.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.772[a]	1	.379		
Continuity Correction[b]	.391	1	.532		
Likelihood Ratio	.762	1	.383		
Fisher's Exact Test				.450	.264
Linear-by-Linear Association	.764	1	.382		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 8.27.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		IPD Dependent	.000	.000
		ECE Dependent	.000	.000
	Goodman and Kruskal tau	IPD Dependent	.008	.019
		ECE Dependent	.008	.019

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		IPD Dependent	.[b]	.[b]
		ECE Dependent	.[b]	.[b]
	Goodman and Kruskal tau	IPD Dependent		.382[c]
		ECE Dependent		.382[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.091	.379
	Cramer's V	.091	.379
N of Valid Cases		94	

IPD * PAR

Crosstab

			PAR		Total
			Absence	Presence	
IPD	Absence	Count	49	8	57
		% within IPD	86.0%	14.0%	100.0%
		% within PAR	65.3%	42.1%	60.6%
		% of Total	52.1%	8.5%	60.6%
		Std. Residual	.5	-1.0	
	Presence	Count	26	11	37
		% within IPD	70.3%	29.7%	100.0%
		% within PAR	34.7%	57.9%	39.4%
		% of Total	27.7%	11.7%	39.4%
		Std. Residual	-.6	1.3	
Total		Count	75	19	94
		% within IPD	79.8%	20.2%	100.0%
		% within PAR	100.0%	100.0%	100.0%
		% of Total	79.8%	20.2%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	3.427[a]	1	.064		
Continuity Correction[b]	2.523	1	.112		
Likelihood Ratio	3.356	1	.067		
Fisher's Exact Test				.073	.057
Linear-by-Linear Association	3.390	1	.066		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 7.48.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.054	.075
		IPD Dependent	.081	.113
		PAR Dependent	.000	.000
	Goodman and Kruskal tau	IPD Dependent	.036	.040
		PAR Dependent	.036	.040

Directional Measures

			Approx. T[b]	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.690	.490
		IPD Dependent	.690	.490
		PAR Dependent	.[c]	.[c]
	Goodman and Kruskal tau	IPD Dependent		.066[d]
		PAR Dependent		.066[d]

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Cannot be computed because the asymptotic standard error equals zero.
d. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.191	.064
	Cramer's V	.191	.064
N of Valid Cases		94	

IPD * GEN

Crosstab

			GEN		Total
			Absence	Presence	
IPD	Absence	Count	31	26	57
		% within IPD	54.4%	45.6%	100.0%
		% within GEN	58.5%	63.4%	60.6%
		% of Total	33.0%	27.7%	60.6%
		Std. Residual	-.2	.2	
	Presence	Count	22	15	37
		% within IPD	59.5%	40.5%	100.0%
		% within GEN	41.5%	36.6%	39.4%
		% of Total	23.4%	16.0%	39.4%
		Std. Residual	.2	-.3	
Total		Count	53	41	94
		% within IPD	56.4%	43.6%	100.0%
		% within GEN	100.0%	100.0%	100.0%
		% of Total	56.4%	43.6%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.235[a]	1	.628		
Continuity Correction[b]	.074	1	.786		
Likelihood Ratio	.235	1	.628		
Fisher's Exact Test				.675	.394
Linear-by-Linear Association	.232	1	.630		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 16.14.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		IPD Dependent	.000	.000
		GEN Dependent	.000	.000
	Goodman and Kruskal tau	IPD Dependent	.002	.010
		GEN Dependent	.002	.010

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		IPD Dependent	.[b]	.[b]
		GEN Dependent	.[b]	.[b]
	Goodman and Kruskal tau	IPD Dependent		.630[c]
		GEN Dependent		.630[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.050	.628
	Cramer's V	.050	.628
N of Valid Cases		94	

GP * NIK

Crosstab

			NIK		Total
			Absence	Presence	
GP	Absence	Count	49	1	50
		% within GP	98.0%	2.0%	100.0%
		% within NIK	54.4%	25.0%	53.2%
		% of Total	52.1%	1.1%	53.2%
		Std. Residual	.2	-.8	
	Presence	Count	41	3	44
		% within GP	93.2%	6.8%	100.0%
		% within NIK	45.6%	75.0%	46.8%
		% of Total	43.6%	3.2%	46.8%
		Std. Residual	-.2	.8	
Total		Count	90	4	94
		% within GP	95.7%	4.3%	100.0%
		% within NIK	100.0%	100.0%	100.0%
		% of Total	95.7%	4.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	1.334[a]	1	.248		
Continuity Correction[b]	.413	1	.520		
Likelihood Ratio	1.375	1	.241		
Fisher's Exact Test				.337	.262
Linear-by-Linear Association	1.319	1	.251		
N of Valid Cases	94				

a. 2 cells (50.0%) have expected count less than 5. The minimum expected count is 1.87.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.042	.040
		GP Dependent	.045	.044
		NIK Dependent	.000	.000
	Goodman and Kruskal tau	GP Dependent	.014	.021
		NIK Dependent	.014	.022

Directional Measures

			Approx. T[b]	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	1.005	.315
		GP Dependent	1.005	.315
		NIK Dependent	.[c]	.[c]
	Goodman and Kruskal tau	GP Dependent		.251[d]
		NIK Dependent		.251[d]

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Cannot be computed because the asymptotic standard error equals zero.
d. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.119	.248
	Cramer's V	.119	.248
N of Valid Cases		94	

GP * ECB

Crosstab

			ECB		Total
			Absence	Presence	
GP	Absence	Count	32	18	50
		% within GP	64.0%	36.0%	100.0%
		% within ECB	52.5%	54.5%	53.2%
		% of Total	34.0%	19.1%	53.2%
		Std. Residual	-.1	.1	
	Presence	Count	29	15	44
		% within GP	65.9%	34.1%	100.0%
		% within ECB	47.5%	45.5%	46.8%
		% of Total	30.9%	16.0%	46.8%
		Std. Residual	.1	-.1	
Total		Count	61	33	94
		% within GP	64.9%	35.1%	100.0%
		% within ECB	100.0%	100.0%	100.0%
		% of Total	64.9%	35.1%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.037[a]	1	.847		
Continuity Correction[b]	.000	1	1.000		
Likelihood Ratio	.037	1	.847		
Fisher's Exact Test				1.000	.510
Linear-by-Linear Association	.037	1	.847		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 15.45.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		GP Dependent	.000	.000
		ECB Dependent	.000	.000
	Goodman and Kruskal tau	GP Dependent	.000	.004
		ECB Dependent	.000	.004

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		GP Dependent	.[b]	.[b]
		ECB Dependent	.[b]	.[b]
	Goodman and Kruskal tau	GP Dependent		.847[c]
		ECB Dependent		.847[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.020	.847
	Cramer's V	.020	.847
N of Valid Cases		94	

GP * MAC

Crosstab

			MAC		Total
			Absence	Presence	
GP	Absence	Count	16	34	50
		% within GP	32.0%	68.0%	100.0%
		% within MAC	50.0%	54.8%	53.2%
		% of Total	17.0%	36.2%	53.2%
		Std. Residual	-.2	.2	
	Presence	Count	16	28	44
		% within GP	36.4%	63.6%	100.0%
		% within MAC	50.0%	45.2%	46.8%
		% of Total	17.0%	29.8%	46.8%
		Std. Residual	.3	-.2	
Total		Count	32	62	94
		% within GP	34.0%	66.0%	100.0%
		% within MAC	100.0%	100.0%	100.0%
		% of Total	34.0%	66.0%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.198[a]	1	.656		
Continuity Correction[b]	.052	1	.820		
Likelihood Ratio	.198	1	.656		
Fisher's Exact Test				.670	.410
Linear-by-Linear Association	.196	1	.658		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 14.98.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		GP Dependent	.000	.000
		MAC Dependent	.000	.000
	Goodman and Kruskal tau	GP Dependent	.002	.009
		MAC Dependent	.002	.009

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		GP Dependent	.[b]	.[b]
		MAC Dependent	.[b]	.[b]
	Goodman and Kruskal tau	GP Dependent		.658[c]
		MAC Dependent		.658[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.046	.656
	Cramer's V	.046	.656
N of Valid Cases		94	

GP * HSS

Crosstab

			HSS		Total
			Absence	Presence	
GP	Absence	Count	13	37	50
		% within GP	26.0%	74.0%	100.0%
		% within HSS	50.0%	54.4%	53.2%
		% of Total	13.8%	39.4%	53.2%
		Std. Residual	-.2	.1	
	Presence	Count	13	31	44
		% within GP	29.5%	70.5%	100.0%
		% within HSS	50.0%	45.6%	46.8%
		% of Total	13.8%	33.0%	46.8%
		Std. Residual	.2	-.1	
Total		Count	26	68	94
		% within GP	27.7%	72.3%	100.0%
		% within HSS	100.0%	100.0%	100.0%
		% of Total	27.7%	72.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.147[a]	1	.701		
Continuity Correction[b]	.023	1	.879		
Likelihood Ratio	.147	1	.702		
Fisher's Exact Test				.818	.439
Linear-by-Linear Association	.145	1	.703		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 12.17.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		GP Dependent	.000	.000
		HSS Dependent	.000	.000
	Goodman and Kruskal tau	GP Dependent	.002	.008
		HSS Dependent	.002	.008

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		GP Dependent	.[b]	.[b]
		HSS Dependent	.[b]	.[b]
	Goodman and Kruskal tau	GP Dependent		.703[c]
		HSS Dependent		.703[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.040	.701
	Cramer's V	.040	.701
N of Valid Cases		94	

GP * FEO

Crosstab

			FEO		Total
			Absence	Presence	
GP	Absence	Count	35	15	50
		% within GP	70.0%	30.0%	100.0%
		% within FEO	50.0%	62.5%	53.2%
		% of Total	37.2%	16.0%	53.2%
		Std. Residual	-.4	.6	
	Presence	Count	35	9	44
		% within GP	79.5%	20.5%	100.0%
		% within FEO	50.0%	37.5%	46.8%
		% of Total	37.2%	9.6%	46.8%
		Std. Residual	.4	-.7	
Total		Count	70	24	94
		% within GP	74.5%	25.5%	100.0%
		% within FEO	100.0%	100.0%	100.0%
		% of Total	74.5%	25.5%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	1.122[a]	1	.290		
Continuity Correction[b]	.676	1	.411		
Likelihood Ratio	1.133	1	.287		
Fisher's Exact Test				.347	.206
Linear-by-Linear Association	1.110	1	.292		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 11.23.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		GP Dependent	.000	.000
		FEO Dependent	.000	.000
	Goodman and Kruskal tau	GP Dependent	.012	.022
		FEO Dependent	.012	.022

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		GP Dependent	.[b]	.[b]
		FEO Dependent	.[b]	.[b]
	Goodman and Kruskal tau	GP Dependent		.292[c]
		FEO Dependent		.292[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.109	.290
	Cramer's V	.109	.290
N of Valid Cases		94	

GP * ECE

Crosstab

			ECE		Total
			Absence	Presence	
GP	Absence	Count	38	12	50
		% within GP	76.0%	24.0%	100.0%
		% within ECE	52.1%	57.1%	53.2%
		% of Total	40.4%	12.8%	53.2%
		Std. Residual	-.1	.2	
	Presence	Count	35	9	44
		% within GP	79.5%	20.5%	100.0%
		% within ECE	47.9%	42.9%	46.8%
		% of Total	37.2%	9.6%	46.8%
		Std. Residual	.1	-.3	
Total		Count	73	21	94
		% within GP	77.7%	22.3%	100.0%
		% within ECE	100.0%	100.0%	100.0%
		% of Total	77.7%	22.3%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.170[a]	1	.680		
Continuity Correction[b]	.027	1	.870		
Likelihood Ratio	.170	1	.680		
Fisher's Exact Test				.805	.436
Linear-by-Linear Association	.168	1	.682		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 9.83.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		GP Dependent	.000	.000
		ECE Dependent	.000	.000
	Goodman and Kruskal tau	GP Dependent	.002	.009
		ECE Dependent	.002	.009

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		GP Dependent	.[b]	.[b]
		ECE Dependent	.[b]	.[b]
	Goodman and Kruskal tau	GP Dependent		.682[c]
		ECE Dependent		.682[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.042	.680
	Cramer's V	.042	.680
N of Valid Cases		94	

GP * PAR

Crosstab

			PAR		Total
			Absence	Presence	
GP	Absence	Count	40	10	50
		% within GP	80.0%	20.0%	100.0%
		% within PAR	53.3%	52.6%	53.2%
		% of Total	42.6%	10.6%	53.2%
		Std. Residual	.0	.0	
	Presence	Count	35	9	44
		% within GP	79.5%	20.5%	100.0%
		% within PAR	46.7%	47.4%	46.8%
		% of Total	37.2%	9.6%	46.8%
		Std. Residual	.0	.0	
Total		Count	75	19	94
		% within GP	79.8%	20.2%	100.0%
		% within PAR	100.0%	100.0%	100.0%
		% of Total	79.8%	20.2%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.003[a]	1	.956		
Continuity Correction[b]	.000	1	1.000		
Likelihood Ratio	.003	1	.956		
Fisher's Exact Test				1.000	.579
Linear-by-Linear Association	.003	1	.957		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 8.89.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		GP Dependent	.000	.000
		PAR Dependent	.000	.000
	Goodman and Kruskal tau	GP Dependent	.000	.001
		PAR Dependent	.000	.001

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		GP Dependent	.[b]	.[b]
		PAR Dependent	.[b]	.[b]
	Goodman and Kruskal tau	GP Dependent		.957[c]
		PAR Dependent		.957[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	.006	.956
	Cramer's V	.006	.956
N of Valid Cases		94	

GP * GEN

Crosstab

			GEN		Total
			Absence	Presence	
GP	Absence	Count	27	23	50
		% within GP	54.0%	46.0%	100.0%
		% within GEN	50.9%	56.1%	53.2%
		% of Total	28.7%	24.5%	53.2%
		Std. Residual	-.2	.3	
	Presence	Count	26	18	44
		% within GP	59.1%	40.9%	100.0%
		% within GEN	49.1%	43.9%	46.8%
		% of Total	27.7%	19.1%	46.8%
		Std. Residual	.2	-.3	
Total		Count	53	41	94
		% within GP	56.4%	43.6%	100.0%
		% within GEN	100.0%	100.0%	100.0%
		% of Total	56.4%	43.6%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	.247[a]	1	.619		
Continuity Correction[b]	.083	1	.773		
Likelihood Ratio	.247	1	.619		
Fisher's Exact Test				.680	.387
Linear-by-Linear Association	.244	1	.621		
N of Valid Cases	94				

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 19.19.
b. Computed only for a 2x2 table

Directional Measures

			Value	Asymp. Std. Error[a]
Nominal by Nominal	Lambda	Symmetric	.000	.000
		GP Dependent	.000	.000
		GEN Dependent	.000	.000
	Goodman and Kruskal tau	GP Dependent	.003	.011
		GEN Dependent	.003	.011

Directional Measures

			Approx. T	Approx. Sig.
Nominal by Nominal	Lambda	Symmetric	.[b]	.[b]
		GP Dependent	.[b]	.[b]
		GEN Dependent	.[b]	.[b]
	Goodman and Kruskal tau	GP Dependent		.621[c]
		GEN Dependent		.621[c]

a. Not assuming the null hypothesis.
b. Cannot be computed because the asymptotic standard error equals zero.
c. Based on chi-square approximation

Symmetric Measures

		Value	Approx. Sig.
Nominal by Nominal	Phi	-.051	.619
	Cramer's V	.051	.619
N of Valid Cases		94	

Appendix F - Bivariate analysis – collinearity diagnostics results

This appendix provides the SPSS Collinearity diagnostics output--tolerance and variance inflation factor (VIF)--to determine which independent variables are highly correlated across case studies.

Regression

Notes

Output Created		10-MAR-2014 01:22:45
Comments		
Input	Data	C:\Users\phil\Desktop\CS_DataAnalysis\CSAanalysis\SPSS_data\CSA1.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	121
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.
Syntax		REGRESSION /MISSING LISTWISE /STATISTICS COLLIN TOL /CRITERIA=PIN(.05) POUT(.10) /NOORIGIN /DEPENDENT NIK /METHOD=ENTER ECB MAC HSS FEO ECE PAR GEN.
Resources	Processor Time	00:00:00.02
	Elapsed Time	00:00:00.05
	Memory Required	6544 bytes
	Additional Memory Required for Residual Plots	0 bytes

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	GEN, PAR, HSS, FEO, ECE, MAC, ECB[b]	.	Enter

a. Dependent Variable: NIK
b. All requested variables entered.

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	ECB	.863	1.159
	MAC	.925	1.081
	HSS	.970	1.031
	FEO	.960	1.042
	ECE	.968	1.033
	PAR	.919	1.088
	GEN	.941	1.062

a. Dependent Variable: NIK

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions							
				(Constant)	ECB	MAC	HSS	FEO	ECE	PAR	GEN
1	1	4.400	1.000	.01	.02	.01	.01	.01	.01	.01	.01
	2	.885	2.230	.00	.01	.00	.00	.22	.08	.49	.01
	3	.756	2.413	.00	.02	.00	.00	.34	.54	.00	.05
	4	.592	2.727	.00	.00	.00	.01	.19	.36	.20	.32
	5	.516	2.921	.03	.63	.07	.07	.01	.01	.01	.06
	6	.461	3.091	.00	.30	.04	.04	.19	.00	.25	.39
	7	.285	3.931	.00	.00	.62	.40	.00	.00	.03	.01
	8	.106	6.433	.96	.02	.26	.48	.04	.00	.01	.14

a. Dependent Variable: NIK

Regression

Notes

Output Created		10-MAR-2014 01:25:27
Comments		
Input	Data	C:\Users\phil\Desktop\CS_DataAnalysis\CSAanalysis\SPSS_data\CSA1.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	121
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.
Syntax		REGRESSION /MISSING LISTWISE /STATISTICS COLLIN TOL /CRITERIA=PIN(.05) POUT(.10) /NOORIGIN /DEPENDENT ECB /METHOD=ENTER MAC HSS FEO ECE PAR GEN NIK.
Resources	Processor Time	00:00:00.02
	Elapsed Time	00:00:00.03
	Memory Required	6544 bytes
	Additional Memory Required for Residual Plots	0 bytes

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	NIK, FEO, HSS, ECE, MAC, GEN, PAR[b]	.	Enter

a. Dependent Variable: ECB
b. All requested variables entered.

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	MAC	.935	1.069
	HSS	.992	1.008
	FEO	.983	1.017
	ECE	.969	1.032
	PAR	.932	1.073
	GEN	.953	1.050
	NIK	.940	1.064

a. Dependent Variable: ECB

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions							
				(Constant)	MAC	HSS	FEO	ECE	PAR	GEN	NIK
1	1	3.993	1.000	.01	.01	.01	.02	.02	.01	.02	.01
	2	1.013	1.985	.00	.00	.00	.09	.04	.16	.00	.52
	3	.797	2.239	.00	.01	.00	.14	.02	.37	.02	.41
	4	.749	2.308	.00	.00	.00	.35	.54	.01	.05	.00
	5	.590	2.602	.01	.00	.02	.21	.37	.18	.30	.01
	6	.470	2.916	.01	.11	.08	.16	.00	.24	.47	.03
	7	.281	3.768	.00	.61	.42	.00	.00	.02	.02	.02
	8	.107	6.110	.97	.25	.46	.03	.00	.01	.13	.01

a. Dependent Variable: ECB

Regression

Notes

Output Created		10-MAR-2014 01:26:43
Comments		
Input	Data	C:\Users\phil\Desktop\CS_DataAnalysis\CSAanalysis\SPSS_data\CSA1.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	121
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.
Syntax		REGRESSION /MISSING LISTWISE /STATISTICS COLLIN TOL /CRITERIA=PIN(.05) POUT(.10) /NOORIGIN /DEPENDENT MAC /METHOD=ENTER HSS FEO ECE PAR GEN NIK ECB.
Resources	Processor Time	00:00:00.02
	Elapsed Time	00:00:00.02
	Memory Required	6544 bytes
	Additional Memory Required for Residual Plots	0 bytes

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	ECB, NIK, ECE, FEO, HSS, GEN, PAR[b]	.	Enter

a. Dependent Variable: MAC
b. All requested variables entered.

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	HSS	.970	1.031
	FEO	.960	1.042
	ECE	.971	1.030
	PAR	.921	1.086
	GEN	.931	1.075
	NIK	.956	1.046
	ECB	.888	1.127

a. Dependent Variable: MAC

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions							
				(Constant)	HSS	FEO	ECE	PAR	GEN	NIK	ECB
1	1	3.802	1.000	.01	.01	.02	.02	.02	.02	.01	.02
	2	1.012	1.938	.00	.00	.09	.03	.15	.00	.55	.00
	3	.798	2.183	.00	.00	.11	.04	.39	.01	.39	.03
	4	.753	2.247	.00	.00	.36	.53	.00	.04	.00	.02
	5	.590	2.538	.01	.01	.20	.36	.18	.31	.01	.01
	6	.492	2.779	.04	.06	.00	.02	.04	.00	.00	.87
	7	.425	2.989	.02	.19	.18	.00	.17	.49	.04	.05
	8	.127	5.464	.93	.71	.04	.00	.04	.13	.00	.00

a. Dependent Variable: MAC

Regression

Notes

Output Created		10-MAR-2014 01:27:27
Comments		
Input	Data	C:\Users\phil\Desktop\CS_DataAnalysis\CSAanalysis\SPSS_data\CSA1.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	121
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.
Syntax		REGRESSION /MISSING LISTWISE /STATISTICS COLLIN TOL /CRITERIA=PIN(.05) POUT(.10) /NOORIGIN /DEPENDENT HSS /METHOD=ENTER FEO ECE PAR GEN NIK ECB MAC.
Resources	Processor Time	00:00:00.03
	Elapsed Time	00:00:00.04
	Memory Required	6544 bytes
	Additional Memory Required for Residual Plots	0 bytes

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	MAC, FEO, GEN, ECE, NIK, PAR, ECB[b]	.	Enter

a. Dependent Variable: HSS
b. All requested variables entered.

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	FEO	.960	1.042
	ECE	.969	1.032
	PAR	.903	1.107
	GEN	.925	1.081
	NIK	.940	1.064
	ECB	.883	1.133
	MAC	.910	1.099

a. Dependent Variable: HSS

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions							
				(Constant)	FEO	ECE	PAR	GEN	NIK	ECB	MAC
1	1	3.796	1.000	.01	.02	.02	.02	.02	.01	.02	.02
	2	1.004	1.945	.00	.11	.05	.15	.00	.50	.00	.00
	3	.802	2.175	.00	.09	.04	.35	.02	.43	.02	.01
	4	.753	2.245	.00	.39	.50	.00	.04	.00	.02	.00
	5	.584	2.550	.00	.15	.34	.14	.38	.01	.05	.00
	6	.483	2.804	.05	.01	.04	.02	.04	.02	.87	.05
	7	.426	2.985	.03	.17	.01	.31	.30	.01	.01	.29
	8	.152	5.000	.91	.06	.00	.01	.20	.02	.01	.64

a. Dependent Variable: HSS

Regression

Notes

Output Created		10-MAR-2014 01:28:08
Comments		
Input	Data	C:\Users\phil\Desktop\CS_DataAnalysis\CSAanalysis\SPSS_data\CSA1.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	121
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.
Syntax		REGRESSION /MISSING LISTWISE /STATISTICS COLLIN TOL /CRITERIA=PIN(.05) POUT(.10) /NOORIGIN /DEPENDENT FEO /METHOD=ENTER ECE PAR GEN NIK ECB MAC HSS.
Resources	Processor Time	00:00:00.03
	Elapsed Time	00:00:00.03
	Memory Required	6544 bytes
	Additional Memory Required for Residual Plots	0 bytes

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	HSS, NIK, ECE, PAR, GEN, MAC, ECB[b]	.	Enter

a. Dependent Variable: FEO
b. All requested variables entered.

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	ECE	.968	1.033
	PAR	.921	1.086
	GEN	.924	1.082
	NIK	.940	1.064
	ECB	.884	1.131
	MAC	.909	1.100
	HSS	.970	1.031

a. Dependent Variable: FEO

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions							
				(Constant)	ECE	PAR	GEN	NIK	ECB	MAC	HSS
1	1	4.207	1.000	.01	.01	.01	.02	.01	.02	.01	.01
	2	.972	2.080	.00	.08	.10	.00	.67	.00	.00	.01
	3	.795	2.300	.00	.27	.33	.06	.24	.03	.01	.00
	4	.637	2.571	.01	.61	.35	.07	.00	.02	.00	.02
	5	.518	2.850	.02	.00	.01	.18	.01	.54	.07	.07
	6	.481	2.957	.00	.02	.17	.52	.05	.39	.02	.01
	7	.281	3.868	.00	.00	.02	.02	.02	.00	.61	.40
	8	.109	6.222	.96	.00	.00	.14	.01	.01	.28	.49

a. Dependent Variable: FEO

Regression

Notes

Output Created		10-MAR-2014 01:29:02
Comments		
Input	Data	C:\Users\phil\Desktop\CS_DataAnalysis\CSAanalysis\SPSS_data\CSA1.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	121
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.
Syntax		REGRESSION /MISSING LISTWISE /STATISTICS COLLIN TOL /CRITERIA=PIN(.05) POUT(.10) /NOORIGIN /DEPENDENT ECE /METHOD=ENTER PAR GEN NIK ECB MAC HSS FEO.
Resources	Processor Time	00:00:00.02
	Elapsed Time	00:00:00.05
	Memory Required	6544 bytes
	Additional Memory Required for Residual Plots	0 bytes

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	FEO, NIK, HSS, GEN, MAC, PAR, ECB[b]	.	Enter

a. Dependent Variable: ECE
b. All requested variables entered.

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	PAR	.903	1.107
	GEN	.940	1.064
	NIK	.940	1.064
	ECB	.864	1.157
	MAC	.913	1.096
	HSS	.971	1.030
	FEO	.960	1.041

a. Dependent Variable: ECE

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions							
				(Constant)	PAR	GEN	NIK	ECB	MAC	HSS	FEO
1	1	4.202	1.000	.01	.01	.02	.01	.02	.01	.01	.01
	2	.997	2.053	.00	.13	.00	.56	.00	.00	.01	.12
	3	.800	2.293	.00	.34	.01	.37	.01	.00	.00	.22
	4	.644	2.554	.00	.19	.34	.01	.00	.00	.01	.42
	5	.516	2.853	.02	.00	.07	.00	.68	.06	.06	.01
	6	.454	3.043	.00	.29	.39	.03	.27	.05	.03	.18
	7	.281	3.866	.00	.02	.02	.02	.00	.60	.41	.00
	8	.105	6.313	.96	.01	.15	.01	.02	.27	.47	.04

a. Dependent Variable: ECE

Regression

Notes

Output Created		10-MAR-2014 01:29:50
Comments		
Input	Data	C:\Users\phil\Desktop\CS_DataAnalysis\CSAanalysis\SPSS_data\CSA1.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	121
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.
Syntax		REGRESSION /MISSING LISTWISE /STATISTICS COLLIN TOL /CRITERIA=PIN(.05) POUT(.10) /NOORIGIN /DEPENDENT PAR /METHOD=ENTER GEN NIK ECB MAC HSS FEO ECE.
Resources	Processor Time	00:00:00.02
	Elapsed Time	00:00:00.03
	Memory Required	6544 bytes
	Additional Memory Required for Residual Plots	0 bytes

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	ECE, NIK, FEO, HSS, MAC, GEN, ECB[b]	.	Enter

a. Dependent Variable: PAR
b. All requested variables entered.

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	GEN	.924	1.082
	NIK	.957	1.045
	ECB	.890	1.123
	MAC	.927	1.078
	HSS	.970	1.031
	FEO	.979	1.022
	ECE	.968	1.033

a. Dependent Variable: PAR

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions							
				(Constant)	GEN	NIK	ECB	MAC	HSS	FEO	ECE
1	1	4.227	1.000	.01	.02	.00	.02	.01	.01	.01	.01
	2	.951	2.108	.00	.00	.88	.00	.00	.00	.04	.01
	3	.755	2.367	.00	.04	.01	.01	.00	.00	.37	.52
	4	.657	2.537	.01	.02	.06	.05	.02	.02	.48	.37
	5	.518	2.857	.02	.30	.00	.38	.10	.06	.02	.00
	6	.502	2.902	.01	.45	.01	.51	.01	.00	.03	.07
	7	.284	3.858	.00	.03	.03	.01	.56	.44	.01	.00
	8	.106	6.308	.96	.14	.01	.01	.29	.47	.03	.00

a. Dependent Variable: PAR

Regression

Notes

Output Created		10-MAR-2014 01:30:34
Comments		
Input	Data	C:\Users\phil\Desktop\CS_DataAnalysis\CSAanalysis\SPSS_data\CSA1.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	121
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.
Syntax		REGRESSION /MISSING LISTWISE /STATISTICS COLLIN TOL /CRITERIA=PIN(.05) POUT(.10) /NOORIGIN /DEPENDENT GEN /METHOD=ENTER NIK ECB MAC HSS FEO ECE PAR.
Resources	Processor Time	00:00:00.03
	Elapsed Time	00:00:00.05
	Memory Required	6544 bytes
	Additional Memory Required for Residual Plots	0 bytes

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	PAR, HSS, ECE, FEO, NIK, MAC, ECB[b]	.	Enter

a. Dependent Variable: GEN

b. All requested variables entered.

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	NIK	.960	1.042
	ECB	.892	1.121
	MAC	.918	1.089
	HSS	.974	1.027
	FEO	.963	1.039
	ECE	.987	1.013
	PAR	.906	1.104

a. Dependent Variable: GEN

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions							
				(Constant)	NIK	ECB	MAC	HSS	FEO	ECE	PAR
1	1	4.013	1.000	.01	.01	.02	.01	.01	.02	.02	.01
	2	1.013	1.990	.00	.53	.00	.00	.00	.09	.04	.15
	3	.797	2.244	.00	.43	.01	.00	.00	.22	.02	.30
	4	.737	2.333	.00	.00	.02	.00	.00	.21	.78	.00
	5	.538	2.732	.03	.00	.07	.05	.09	.32	.13	.32
	6	.500	2.834	.01	.01	.87	.00	.00	.12	.00	.18
	7	.284	3.760	.00	.01	.00	.67	.36	.00	.00	.03
	8	.119	5.805	.95	.00	.00	.26	.53	.03	.01	.01

a. Dependent Variable: GEN

Appendix G - Binary logistic regression analysis results

This appendix provides the SPSS output of the backward stepwise (likelihood ratio) method of binary logistic regression used to examine the relationships between the dependent (adaptation response option) variables and the independent (driving factor) variables.

Notes

Output Created		14-MAR-2014 04:41:28
Comments		
Input	Data	C:\Users\phil\Desktop\CS_DataAnalysis\CSAanalysis\SPSS_data\CSA1.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	121
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing
Syntax		LOGISTIC REGRESSION VARIABLES AC /METHOD=BSTEP(LR) ECB MAC HSS FEO ECE PAR /CONTRAST (ECB)=Indicator(1) /CONTRAST (MAC)=Indicator(1) /CONTRAST (HSS)=Indicator(1) /CONTRAST (FEO)=Indicator(1) /CONTRAST (ECE)=Indicator(1) /CONTRAST (PAR)=Indicator(1) /SAVE=PRED ZRESID /CLASSPLOT /CASEWISE OUTLIER(2) /PRINT=GOODFIT CI(95) /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).
Resources	Processor Time	00:00:00.08
	Elapsed Time	00:00:00.07
Variables Created or Modified	PRE_1	Predicted probability
	ZRE_1	Normalized residual

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	94	77.7
	Missing Cases	27	22.3
	Total	121	100.0
Unselected Cases		0	.0
Total		121	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
Absence	0
Presence	1

Categorical Variables Codings

		Frequency	Parameter coding (1)
PAR	Absence	75	.000
	Presence	19	1.000
MAC	Absence	32	.000
	Presence	62	1.000
HSS	Absence	26	.000
	Presence	68	1.000
FEO	Absence	70	.000
	Presence	24	1.000
ECE	Absence	73	.000
	Presence	21	1.000
ECB	Absence	61	.000
	Presence	33	1.000

Block 0: Beginning Block

Classification Table[a,b]

	Observed		Predicted AC Absence	Predicted AC Presence	Predicted Percentage Correct
Step 0	AC	Absence	0	10	.0
		Presence	0	84	100.0
	Overall Percentage				89.4

a. Constant is included in the model.
b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	2.128	.335	40.475	1	.000	8.400

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	ECB(1)	1.121	1	.290
		MAC(1)	3.358	1	.067
		HSS(1)	2.791	1	.095
		FEO(1)	1.420	1	.233
		ECE(1)	.982	1	.322
		PAR(1)	2.717	1	.099
	Overall Statistics		11.728	6	.068

Block 1: Method = Backward Stepwise (Likelihood Ratio)

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	11.195	6	.083
	Block	11.195	6	.083
	Model	11.195	6	.083
Step 2[a]	Step	-.170	1	.680
	Block	11.025	5	.051
	Model	11.025	5	.051
Step 3[a]	Step	-.737	1	.391
	Block	10.288	4	.036
	Model	10.288	4	.036
Step 4[a]	Step	-.879	1	.348
	Block	9.408	3	.024
	Model	9.408	3	.024
Step 5[a]	Step	-1.977	1	.160
	Block	7.431	2	.024
	Model	7.431	2	.024

a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	52.515[a]	.112	.228
2	52.686[a]	.111	.225
3	53.423[a]	.104	.211
4	54.302[a]	.095	.193
5	56.279[a]	.076	.154

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	4.580	8	.801
2	8.319	8	.403
3	5.584	6	.471
4	3.794	4	.435
5	.681	2	.712

Contingency Table for Hosmer and Lemeshow Test

		AC = Absence		AC = Presence		
		Observed	Expected	Observed	Expected	Total
Step 1	1	3	3.774	6	5.226	9
	2	1	.833	4	4.167	5
	3	1	1.690	10	9.310	11
	4	2	1.196	8	8.804	10
	5	2	.862	8	9.138	10
	6	1	.509	8	8.491	9
	7	0	.136	3	2.864	3
	8	0	.560	13	12.440	13
	9	0	.266	11	10.734	11
	10	0	.174	13	12.826	13
Step 2	1	3	3.696	6	5.304	9
	2	1	.793	4	4.207	5
	3	2	1.878	11	11.122	13
	4	1	1.150	7	6.850	8
	5	3	.828	6	8.172	9
	6	0	.561	9	8.439	9
	7	0	.159	4	3.841	4
	8	0	.620	17	16.380	17
	9	0	.202	11	10.798	11
	10	0	.113	9	8.887	9
Step 3	1	3	4.285	9	7.715	12
	2	2	1.725	11	11.275	13
	3	3	1.789	11	12.211	14
	4	2	.722	7	8.278	9
	5	0	.487	9	8.513	9
	6	0	.131	4	3.869	4
	7	0	.749	24	23.251	24
	8	0	.111	9	8.889	9
Step 4	1	3	2.485	3	3.515	6
	2	1	2.043	7	5.957	8
	3	1	1.515	12	11.485	13
	4	3	2.283	18	18.717	21
	5	2	.861	11	12.139	13
	6	0	.812	33	32.188	33
Step 5	1	2	1.503	1	1.497	3
	2	2	2.497	14	13.503	16
	3	4	4.497	25	24.503	29
	4	2	1.503	44	44.497	46

Classification Table[a]

	Observed		Predicted AC Absence	Predicted AC Presence	Percentage Correct
Step 1	AC	Absence	1	9	10.0
		Presence	1	83	98.8
	Overall Percentage				89.4
Step 2	AC	Absence	1	9	10.0
		Presence	1	83	98.8
	Overall Percentage				89.4
Step 3	AC	Absence	1	9	10.0
		Presence	1	83	98.8
	Overall Percentage				89.4
Step 4	AC	Absence	1	9	10.0
		Presence	1	83	98.8
	Overall Percentage				89.4
Step 5	AC	Absence	2	8	20.0
		Presence	1	83	98.8
	Overall Percentage				90.4

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	ECB(1)	.382	.939	.165	1	.684	1.465	.233	9.225
	MAC(1)	1.395	.818	2.908	1	.088	4.036	.812	20.061
	HSS(1)	.942	.762	1.528	1	.216	2.566	.576	11.431
	FEO(1)	.891	1.124	.628	1	.428	2.437	.269	22.046
	ECE(1)	.881	1.131	.607	1	.436	2.413	.263	22.126
	PAR(1)	-1.518	.844	3.236	1	.072	.219	.042	1.145
	Constant	.764	.695	1.208	1	.272	2.147		
Step 2[a]	MAC(1)	1.495	.787	3.603	1	.058	4.458	.953	20.866
	HSS(1)	1.024	.736	1.940	1	.164	2.786	.659	11.777
	FEO(1)	.950	1.117	.723	1	.395	2.585	.290	23.062
	ECE(1)	.889	1.129	.620	1	.431	2.433	.266	22.237
	PAR(1)	-1.489	.840	3.144	1	.076	.226	.044	1.170
	Constant	.755	.688	1.201	1	.273	2.127		
Step 3[a]	MAC(1)	1.514	.791	3.666	1	.056	4.547	.965	21.427
	HSS(1)	.996	.734	1.842	1	.175	2.707	.643	11.402
	FEO(1)	.948	1.111	.728	1	.393	2.582	.292	22.802
	PAR(1)	-1.553	.833	3.472	1	.062	.212	.041	1.084
	Constant	.925	.646	2.047	1	.153	2.521		
Step 4[a]	MAC(1)	1.576	.788	3.996	1	.046	4.835	1.031	22.667
	HSS(1)	1.034	.725	2.031	1	.154	2.812	.679	11.650
	PAR(1)	-1.654	.829	3.984	1	.046	.191	.038	.971
	Constant	1.070	.634	2.853	1	.091	2.915		

Variables in the Equation (continued)

Step 5[a]	MAC(1)	1.692	.789	4.596	1	.032	5.432	1.156	25.521
	PAR(1)	-1.700	.820	4.296	1	.038	.183	.037	.912
	Constant	1.695	.488	12.074	1	.001	5.449		

a. Variable(s) entered on step 1: ECB, MAC, HSS, FEO, ECE, PAR.

Model if Term Removed

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	ECB	-26.343	.170	1	.680
	MAC	-27.820	3.124	1	.077
	HSS	-27.003	1.492	1	.222
	FEO	-26.630	.745	1	.388
	ECE	-26.617	.720	1	.396
	PAR	-27.868	3.220	1	.073
Step 2	MAC	-28.291	3.897	1	.048
	HSS	-27.289	1.893	1	.169
	FEO	-26.778	.871	1	.351
	ECE	-26.711	.737	1	.391
	PAR	-27.910	3.133	1	.077
Step 3	MAC	-28.695	3.966	1	.046
	HSS	-27.609	1.794	1	.180
	FEO	-27.151	.879	1	.348
	PAR	-28.445	3.468	1	.063
Step 4	MAC	-29.333	4.364	1	.037
	HSS	-28.140	1.977	1	.160
	PAR	-29.132	3.962	1	.047
Step 5	MAC	-30.686	5.093	1	.024
	PAR	-30.274	4.269	1	.039

Variables not in the Equation

			Score	df	Sig.
Step 2[a]	Variables	ECB(1)	.166	1	.683
	Overall Statistics		.166	1	.683
Step 3[b]	Variables	ECB(1)	.184	1	.668
		ECE(1)	.653	1	.419
	Overall Statistics		.822	2	.663
Step 4[c]	Variables	ECB(1)	.331	1	.565
		FEO(1)	.776	1	.378
		ECE(1)	.658	1	.417
	Overall Statistics		1.548	3	.671
Step 5[d]	Variables	ECB(1)	.845	1	.358
		HSS(1)	2.136	1	.144
		FEO(1)	.926	1	.336
		ECE(1)	.642	1	.423
	Overall Statistics		3.527	4	.474

a. Variable(s) removed on step 2: ECB.
b. Variable(s) removed on step 3: ECE.
c. Variable(s) removed on step 4: FEO.

d. Variable(s) removed on step 5: HSS.

Casewise List[b]

Case	Selected Status[a]	Observed AC	Predicted	Predicted Group	Temporary Variable Resid	Temporary Variable ZResid
58	S	A**	.967	P	-.967	-5.441
107	S	A**	.967	P	-.967	-5.441

a. S = Selected, U = Unselected cases, and ** = Misclassified cases.
b. Cases with studentized residuals greater than 2.000 are listed.

Logistic Regression

Notes

Output Created		14-MAR-2014 04:41:49
Comments		
Input	Data	C:\Users\phil\Desktop\CS_DataAnalysis\CSAanalysis\SPSS_data\CSA1.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	121
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing
Syntax		LOGISTIC REGRESSION VARIABLES MC /METHOD=BSTEP(LR) ECB MAC HSS FEO ECE PAR /CONTRAST (ECB)=Indicator(1) /CONTRAST (MAC)=Indicator(1) /CONTRAST (HSS)=Indicator(1) /CONTRAST (FEO)=Indicator(1) /CONTRAST (ECE)=Indicator(1) /CONTRAST (PAR)=Indicator(1) /SAVE=PRED ZRESID /CLASSPLOT /CASEWISE OUTLIER(2) /PRINT=GOODFIT CI(95) /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).
Resources	Processor Time	00:00:00.05
	Elapsed Time	00:00:00.09
Variables Created or Modified	PRE_2	Predicted probability
	ZRE_2	Normalized residual

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	94	77.7
	Missing Cases	27	22.3
	Total	121	100.0
Unselected Cases		0	.0
Total		121	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
Absence	0
Presence	1

Categorical Variables Codings

		Frequency	Parameter coding (1)
PAR	Absence	75	.000
	Presence	19	1.000
MAC	Absence	32	.000
	Presence	62	1.000
HSS	Absence	26	.000
	Presence	68	1.000
FEO	Absence	70	.000
	Presence	24	1.000
ECE	Absence	73	.000
	Presence	21	1.000
ECB	Absence	61	.000
	Presence	33	1.000

Block 0: Beginning Block

Classification Table[a,b]

	Observed		Predicted MC Absence	Predicted MC Presence	Percentage Correct
Step 0	MC	Absence	0	47	.0
		Presence	0	47	100.0
	Overall Percentage				50.0

a. Constant is included in the model.
b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	.000	.206	.000	1	1.000	1.000

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	ECB(1)	5.650	1	.017
		MAC(1)	4.738	1	.030
		HSS(1)	3.403	1	.065
		FEO(1)	.895	1	.344
		ECE(1)	.061	1	.804
		PAR(1)	3.232	1	.072
	Overall Statistics		16.004	6	.014

Block 1: Method = Backward Stepwise (Likelihood Ratio)

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	17.032	6	.009
	Block	17.032	6	.009
	Model	17.032	6	.009
Step 2[a]	Step	-.192	1	.662
	Block	16.840	5	.005
	Model	16.840	5	.005
Step 3[a]	Step	-.847	1	.357
	Block	15.993	4	.003
	Model	15.993	4	.003
Step 4[a]	Step	-1.119	1	.290
	Block	14.874	3	.002
	Model	14.874	3	.002

a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	113.280[a]	.166	.221
2	113.472[a]	.164	.219
3	114.319[a]	.156	.209
4	115.438[a]	.146	.195

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	6.443	7	.489
2	5.162	7	.640
3	8.014	7	.331
4	10.434	5	.064

Contingency Table for Hosmer and Lemeshow Test

		MC = Absence		MC = Presence		Total
		Observed	Expected	Observed	Expected	
Step 1	1	11	9.771	1	2.229	12
	2	6	5.708	2	2.292	8
	3	9	8.420	4	4.580	13
	4	4	5.887	6	4.113	10
	5	4	4.689	5	4.311	9
	6	3	3.857	6	5.143	9
	7	5	3.489	5	6.511	10
	8	1	2.638	9	7.362	10
	9	4	2.540	9	10.460	13
Step 2	1	11	9.823	1	2.177	12
	2	4	2.899	0	1.101	4
	3	11	11.227	6	5.773	17
	4	4	5.231	5	3.769	9
	5	4	4.745	5	4.255	9
	6	3	3.906	6	5.094	9
	7	2	2.985	6	5.015	8
	8	4	3.597	9	9.403	13
	9	4	2.588	9	10.412	13
Step 3	1	14	11.984	1	3.016	15
	2	1	.683	0	.317	1
	3	13	13.920	9	8.080	22
	4	2	3.457	4	2.543	6
	5	6	5.252	4	4.748	10
	6	3	4.864	10	8.136	13
	7	2	3.009	7	5.991	9
	8	3	2.425	7	7.575	10
	9	3	1.405	5	6.595	8
Step 4	1	15	12.710	1	3.290	16
	2	15	15.161	10	9.839	25
	3	2	3.287	4	2.713	6
	4	4	4.744	5	4.256	9
	5	6	6.842	15	14.158	21
	6	2	3.385	9	7.615	11
	7	3	.871	3	5.129	6

Classification Table[a]

	Observed		Predicted MC Absence	Predicted MC Presence	Percentage Correct
Step 1	MC	Absence	33	14	70.2
		Presence	16	31	66.0
	Overall Percentage				68.1
Step 2	MC	Absence	34	13	72.3
		Presence	17	30	63.8
	Overall Percentage				68.1
Step 3	MC	Absence	34	13	72.3
		Presence	17	30	63.8
	Overall Percentage				68.1
Step 4	MC	Absence	36	11	76.6
		Presence	20	27	57.4
	Overall Percentage				67.0

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	ECB(1)	1.017	.505	4.060	1	.044	2.765	1.028	7.435
	MAC(1)	.851	.496	2.940	1	.086	2.341	.885	6.190
	HSS(1)	-1.225	.534	5.271	1	.022	.294	.103	.836
	FEO(1)	.481	.531	.822	1	.365	1.618	.572	4.582
	ECE(1)	-.236	.540	.191	1	.662	.790	.274	2.278
	PAR(1)	.680	.593	1.313	1	.252	1.974	.617	6.315
	Constant	-.234	.541	.188	1	.665	.791		
Step 2[a]	ECB(1)	1.001	.502	3.978	1	.046	2.720	1.017	7.273
	MAC(1)	.842	.495	2.887	1	.089	2.320	.879	6.125
	HSS(1)	-1.229	.532	5.347	1	.021	.293	.103	.829
	FEO(1)	.485	.530	.838	1	.360	1.625	.575	4.594
	PAR(1)	.691	.592	1.361	1	.243	1.995	.625	6.369
	Constant	-.278	.530	.275	1	.600	.757		
Step 3[a]	ECB(1)	1.073	.496	4.678	1	.031	2.923	1.106	7.726
	MAC(1)	.836	.492	2.888	1	.089	2.307	.880	6.049
	HSS(1)	-1.207	.526	5.269	1	.022	.299	.107	.838
	PAR(1)	.610	.584	1.092	1	.296	1.841	.586	5.780
	Constant	-.173	.513	.113	1	.737	.842		
Step 4[a]	ECB(1)	1.160	.490	5.598	1	.018	3.188	1.220	8.332
	MAC(1)	.919	.485	3.585	1	.058	2.507	.968	6.492
	HSS(1)	-1.243	.530	5.511	1	.019	.289	.102	.814
	Constant	-.108	.509	.045	1	.831	.897		

a. Variable(s) entered on step 1: ECB, MAC, HSS, FEO, ECE, PAR.

Model if Term Removed

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	ECB	-58.742	4.203	1	.040
	MAC	-58.151	3.022	1	.082
	HSS	-59.480	5.681	1	.017
	FEO	-57.056	.831	1	.362
	ECE	-56.736	.192	1	.662
	PAR	-57.315	1.350	1	.245
Step 2	ECB	-58.790	4.107	1	.043
	MAC	-58.219	2.967	1	.085
	HSS	-59.620	5.768	1	.016
	FEO	-57.160	.847	1	.357
	PAR	-57.435	1.399	1	.237
Step 3	ECB	-59.591	4.863	1	.027
	MAC	-58.645	2.970	1	.085
	HSS	-59.988	5.656	1	.017
	PAR	-57.719	1.119	1	.290
Step 4	ECB	-60.662	5.885	1	.015
	MAC	-59.574	3.710	1	.054
	HSS	-60.689	5.940	1	.015

Variables not in the Equation

			Score	df	Sig.
Step 2[a]	Variables	ECE(1)	.191	1	.662
	Overall Statistics		.191	1	.662
Step 3[b]	Variables	FEO(1)	.845	1	.358
		ECE(1)	.208	1	.649
	Overall Statistics		1.034	2	.596
Step 4[c]	Variables	FEO(1)	.566	1	.452
		ECE(1)	.247	1	.619
		PAR(1)	1.108	1	.293
	Overall Statistics		2.143	3	.543

a. Variable(s) removed on step 2: ECE.
b. Variable(s) removed on step 3: FEO.
c. Variable(s) removed on step 4: PAR.

Casewise List[b]

Case	Selected Status[a]	Observed MC	Predicted	Predicted Group	Temporary Variable Resid	Temporary Variable ZResid
34	S	A**	.878	P	-.878	-2.678
39	S	A**	.878	P	-.878	-2.678
68	S	A**	.878	P	-.878	-2.678

a. S = Selected, U = Unselected cases, and ** = Misclassified cases.
b. Cases with studentized residuals greater than 2.000 are listed.

Logistic Regression

Notes

Output Created		14-MAR-2014 04:42:13
Comments		
Input	Data	C:\Users\phil\Desktop\CS_DataAnalysis\CSAanalysis\SPSS_data\CSA1.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	121
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing
Syntax		LOGISTIC REGRESSION VARIABLES IPD /METHOD=BSTEP(LR) ECB MAC HSS FEO ECE PAR /CONTRAST (ECB)=Indicator(1) /CONTRAST (MAC)=Indicator(1) /CONTRAST (HSS)=Indicator(1) /CONTRAST (FEO)=Indicator(1) /CONTRAST (ECE)=Indicator(1) /CONTRAST (PAR)=Indicator(1) /SAVE=PRED ZRESID /CLASSPLOT /CASEWISE OUTLIER(2) /PRINT=GOODFIT CI(95) /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).
Resources	Processor Time	00:00:00.08
	Elapsed Time	00:00:00.07
Variables Created or Modified	PRE_3	Predicted probability
	ZRE_3	Normalized residual

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	94	77.7
	Missing Cases	27	22.3
	Total	121	100.0
Unselected Cases		0	.0
Total		121	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
Absence	0
Presence	1

Categorical Variables Codings

		Frequency	Parameter coding (1)
PAR	Absence	75	.000
	Presence	19	1.000
MAC	Absence	32	.000
	Presence	62	1.000
HSS	Absence	26	.000
	Presence	68	1.000
FEO	Absence	70	.000
	Presence	24	1.000
ECE	Absence	73	.000
	Presence	21	1.000
ECB	Absence	61	.000
	Presence	33	1.000

Block 0: Beginning Block

Classification Table[a,b]

	Observed		Predicted		
			IPD		Percentage Correct
			Absence	Presence	
Step 0	IPD	Absence	57	0	100.0
		Presence	37	0	.0
	Overall Percentage				60.6

a. Constant is included in the model.

b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.432	.211	4.190	1	.041	.649

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	ECB(1)	.192	1	.662
		MAC(1)	3.850	1	.050
		HSS(1)	2.330	1	.127
		FEO(1)	1.403	1	.236
		ECE(1)	.772	1	.379
		PAR(1)	3.427	1	.064
	Overall Statistics		14.030	6	.029

Block 1: Method = Backward Stepwise (Likelihood Ratio)

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	15.186	6	.019
	Block	15.186	6	.019
	Model	15.186	6	.019
Step 2[a]	Step	-.464	1	.496
	Block	14.721	5	.012
	Model	14.721	5	.012
Step 3[a]	Step	-1.247	1	.264
	Block	13.475	4	.009
	Model	13.475	4	.009
Step 4[a]	Step	-1.181	1	.277
	Block	12.293	3	.006
	Model	12.293	3	.006

a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	110.838[a]	.149	.202
2	111.302[a]	.145	.196
3	112.549[a]	.134	.181
4	113.730[a]	.123	.166

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	8.557	8	.381
2	5.412	8	.713
3	2.292	7	.942
4	.099	4	.999

Contingency Table for Hosmer and Lemeshow Test

		IPD = Absence		IPD = Presence		
		Observed	Expected	Observed	Expected	Total
Step 1	1	8	7.251	0	.749	8
	2	6	6.824	2	1.176	8
	3	5	7.010	4	1.990	9
	4	13	10.498	2	4.502	15
	5	6	6.403	4	3.597	10
	6	5	5.088	4	3.912	9
	7	5	3.409	2	3.591	7
	8	3	3.563	5	4.437	8
	9	3	4.351	8	6.649	11
	10	3	2.604	6	6.396	9
Step 2	1	10	10.600	2	1.400	12
	2	6	7.319	3	1.681	9
	3	3	2.206	0	.794	3
	4	14	12.194	3	4.806	17
	5	3	3.891	3	2.109	6
	6	4	4.063	3	2.937	7
	7	6	4.885	3	4.115	9
	8	6	6.194	9	8.806	15
	9	4	3.705	5	5.295	9
	10	1	1.943	6	5.057	7
Step 3	1	9	9.702	2	1.298	11
	2	2	1.613	0	.387	2
	3	18	17.955	6	6.045	24
	4	5	5.364	3	2.636	8
	5	6	5.614	3	3.386	9
	6	2	1.615	1	1.385	3
	7	8	8.169	10	9.831	18
	8	5	3.927	4	5.073	9
	9	2	3.041	8	6.959	10
Step 4	1	11	11.225	2	1.775	13
	2	24	23.614	9	9.386	33
	3	5	5.210	3	2.790	8
	4	2	1.894	1	1.106	3
	5	9	8.951	12	12.049	21
	6	6	6.106	10	9.894	16

Classification Table[a]

	Observed		Predicted IPD Absence	Predicted IPD Presence	Percentage Correct
Step 1	IPD	Absence	43	14	75.4
		Presence	16	21	56.8
	Overall Percentage				68.1
Step 2	IPD	Absence	46	11	80.7
		Presence	17	20	54.1
	Overall Percentage				70.2
Step 3	IPD	Absence	42	15	73.7
		Presence	15	22	59.5
	Overall Percentage				68.1
Step 4	IPD	Absence	42	15	73.7
		Presence	15	22	59.5
	Overall Percentage				68.1

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	ECB(1)	-.357	.528	.458	1	.499	.700	.249	1.969
	MAC(1)	-1.241	.505	6.037	1	.014	.289	.107	.778
	HSS(1)	1.044	.577	3.275	1	.070	2.839	.917	8.790
	FEO(1)	-.540	.561	.928	1	.335	.583	.194	1.748
	ECE(1)	.635	.541	1.374	1	.241	1.887	.653	5.451
	PAR(1)	1.382	.598	5.339	1	.021	3.982	1.233	12.856
	Constant	-.619	.563	1.211	1	.271	.538		
Step 2[a]	MAC(1)	-1.283	.499	6.607	1	.010	.277	.104	.737
	HSS(1)	.966	.558	3.000	1	.083	2.628	.881	7.844
	FEO(1)	-.607	.553	1.203	1	.273	.545	.184	1.612
	ECE(1)	.607	.538	1.272	1	.259	1.835	.639	5.265
	PAR(1)	1.288	.578	4.960	1	.026	3.626	1.167	11.268
	Constant	-.614	.557	1.217	1	.270	.541		
Step 3[a]	MAC(1)	-1.274	.495	6.620	1	.010	.280	.106	.738
	HSS(1)	.923	.549	2.825	1	.093	2.516	.858	7.378
	ECE(1)	.583	.537	1.180	1	.277	1.792	.626	5.130
	PAR(1)	1.345	.572	5.529	1	.019	3.836	1.251	11.766
	Constant	-.737	.544	1.838	1	.175	.478		
Step 4[a]	MAC(1)	-1.220	.489	6.225	1	.013	.295	.113	.770
	HSS(1)	.922	.544	2.872	1	.090	2.513	.866	7.297
	PAR(1)	1.307	.565	5.354	1	.021	3.694	1.221	11.171
	Constant	-.624	.531	1.382	1	.240	.536		

a. Variable(s) entered on step 1: ECB, MAC, HSS, FEO, ECE, PAR.

Model if Term Removed

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	ECB	-55.651	.464	1	.496
	MAC	-58.583	6.328	1	.012
	HSS	-57.211	3.584	1	.058
	FEO	-55.897	.956	1	.328
	ECE	-56.108	1.379	1	.240
	PAR	-58.222	5.606	1	.018
Step 2	MAC	-59.143	6.984	1	.008
	HSS	-57.270	3.238	1	.072
	FEO	-56.275	1.247	1	.264
	ECE	-56.288	1.275	1	.259
	PAR	-58.233	5.165	1	.023
Step 3	MAC	-59.767	6.985	1	.008
	HSS	-57.790	3.031	1	.082
	ECE	-56.865	1.181	1	.277
	PAR	-59.163	5.777	1	.016
Step 4	MAC	-60.128	6.527	1	.011
	HSS	-58.407	3.083	1	.079
	PAR	-59.648	5.565	1	.018

Variables not in the Equation

			Score	df	Sig.
Step 2[a]	Variables	ECB(1)	.460	1	.498
	Overall Statistics		.460	1	.498
Step 3[b]	Variables	ECB(1)	.745	1	.388
		FEO(1)	1.219	1	.269
	Overall Statistics		1.676	2	.433
Step 4[c]	Variables	ECB(1)	.600	1	.439
		FEO(1)	1.130	1	.288
		ECE(1)	1.195	1	.274
	Overall Statistics		2.863	3	.413

a. Variable(s) removed on step 2: ECB.
b. Variable(s) removed on step 3: FEO.
c. Variable(s) removed on step 4: ECE.

Casewise List[b]

Case	Selected Status[a]	Observed	Predicted	Predicted Group	Temporary Variable	
		IPD			Resid	ZResid
107	S	P**	.137	A	.863	2.515
108	S	P**	.137	A	.863	2.515

a. S = Selected, U = Unselected cases, and ** = Misclassified cases.
b. Cases with studentized residuals greater than 2.000 are listed.

Logistic Regression

Notes

Output Created		14-MAR-2014 04:42:33
Comments		
Input	Data	C:\Users\phil\Desktop\CS_DataAnalysis\CSAanalysis\SPSS_data\CSA1.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	121
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing
Syntax		LOGISTIC REGRESSION VARIABLES GP /METHOD=BSTEP(LR) ECB MAC HSS FEO ECE PAR /CONTRAST (ECB)=Indicator(1) /CONTRAST (MAC)=Indicator(1) /CONTRAST (HSS)=Indicator(1) /CONTRAST (FEO)=Indicator(1) /CONTRAST (ECE)=Indicator(1) /CONTRAST (PAR)=Indicator(1) /SAVE=PRED ZRESID /CLASSPLOT /CASEWISE OUTLIER(2) /PRINT=GOODFIT CI(95) /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).
Resources	Processor Time	00:00:00.11
	Elapsed Time	00:00:00.09
Variables Created or Modified	PRE_4	Predicted probability
	ZRE_4	Normalized residual

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	94	77.7
	Missing Cases	27	22.3
	Total	121	100.0
Unselected Cases		0	.0
Total		121	100.0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
Absence	0
Presence	1

Categorical Variables Codings

		Frequency	Parameter coding
			(1)
PAR	Absence	75	.000
	Presence	19	1.000
MAC	Absence	32	.000
	Presence	62	1.000
HSS	Absence	26	.000
	Presence	68	1.000
FEO	Absence	70	.000
	Presence	24	1.000
ECE	Absence	73	.000
	Presence	21	1.000
ECB	Absence	61	.000
	Presence	33	1.000

Block 0: Beginning Block

Classification Table[a,b]

	Observed		Predicted		
			GP		Percentage Correct
			Absence	Presence	
Step 0	GP	Absence	50	0	100.0
		Presence	44	0	.0
	Overall Percentage				53.2

a. Constant is included in the model.
b. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.128	.207	.382	1	.536	.880

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	ECB(1)	.037	1	.847
		MAC(1)	.198	1	.656
		HSS(1)	.147	1	.701
		FEO(1)	1.122	1	.290
		ECE(1)	.170	1	.680
		PAR(1)	.003	1	.956
	Overall Statistics		1.537	6	.957

Block 1: Method = Backward Stepwise (Likelihood Ratio)

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	1.554	6	.956
	Block	1.554	6	.956
	Model	1.554	6	.956
Step 2[a]	Step	.000	1	.997
	Block	1.554	5	.907
	Model	1.554	5	.907
Step 3[a]	Step	-.011	1	.917
	Block	1.543	4	.819
	Model	1.543	4	.819
Step 4[a]	Step	-.096	1	.757
	Block	1.447	3	.695
	Model	1.447	3	.695
Step 5[a]	Step	-.122	1	.727
	Block	1.325	2	.516
	Model	1.325	2	.516
Step 6[a]	Step	-.192	1	.661
	Block	1.133	1	.287
	Model	1.133	1	.287
Step 7[a]	Step	-1.133	1	.287

a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	128.375[a]	.016	.022
2	128.375[a]	.016	.022
3	128.386[a]	.016	.022
4	128.481[a]	.015	.020
5	128.603[a]	.014	.019
6	128.796[a]	.012	.016
7	129.928[b]	.000	.000

a. Estimation terminated at iteration number 3 because parameter estimates changed by less than .001.
b. Estimation terminated at iteration number 2 because parameter estimates changed by less than .001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	8.428	8	.393
2	5.817	7	.561
3	3.026	7	.883
4	1.036	5	.960
5	.600	2	.741
6	.000	0	.
7	.000	0	.

Contingency Table for Hosmer and Lemeshow Test

		GP = Absence		GP = Presence		Total
		Observed	Expected	Observed	Expected	
Step 1	1	7	5.885	2	3.115	9
	2	6	5.597	3	3.403	9
	3	3	5.786	7	4.214	10
	4	4	4.360	4	3.640	8
	5	9	6.773	4	6.227	13
	6	4	4.084	4	3.916	8
	7	3	4.936	7	5.064	10
	8	3	1.916	1	2.084	4
	9	6	5.225	5	5.775	11
	10	5	5.437	7	6.563	12
Step 2	1	7	5.884	2	3.116	9
	2	6	5.598	3	3.402	9
	3	3	5.786	7	4.214	10
	4	4	3.839	3	3.161	7
	5	9	7.295	5	6.705	14
	6	5	6.119	7	5.881	12
	7	4	4.341	5	4.659	9
	8	7	5.700	5	6.300	12
	9	5	5.437	7	6.563	12
Step 3	1	8	7.771	4	4.229	12
	2	7	6.668	4	4.332	11
	3	5	6.144	6	4.856	11
	4	0	.523	1	.477	1
	5	14	12.906	11	12.094	25
	6	4	5.317	7	5.683	11
	7	2	1.436	1	1.564	3
	8	7	6.614	7	7.386	14
	9	3	2.620	3	3.380	6
Step 4	1	3	2.677	1	1.323	4
	2	8	7.553	4	4.447	12
	3	4	4.770	4	3.230	8
	4	5	6.050	6	4.950	11
	5	18	17.720	17	17.280	35
	6	2	2.018	2	1.982	4
	7	10	9.212	10	10.788	20
Step 5	1	11	10.242	5	5.758	16
	2	4	4.758	4	3.242	8
	3	23	23.758	23	22.242	46
	4	12	11.242	12	12.758	24
Step 6	1	15	15.000	9	9.000	24
	2	35	35.000	35	35.000	70
Step 7	1	50	50.000	44	44.000	94

Classification Table[a]

	Observed		Predicted GP Absence	Predicted GP Presence	Percentage Correct
Step 1	GP	Absence	34	16	68.0
		Presence	27	17	38.6
	Overall Percentage				54.3
Step 2	GP	Absence	34	16	68.0
		Presence	27	17	38.6
	Overall Percentage				54.3
Step 3	GP	Absence	34	16	68.0
		Presence	27	17	38.6
	Overall Percentage				54.3
Step 4	GP	Absence	40	10	80.0
		Presence	34	10	22.7
	Overall Percentage				53.2
Step 5	GP	Absence	38	12	76.0
		Presence	32	12	27.3
	Overall Percentage				53.2
Step 6	GP	Absence	15	35	30.0
		Presence	9	35	79.5
	Overall Percentage				53.2
Step 7	GP	Absence	50	0	100.0
		Presence	44	0	.0
	Overall Percentage				53.2

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	ECB(1)	.048	.463	.011	1	.917	1.049	.423	2.600
	MAC(1)	-.184	.455	.164	1	.686	.832	.341	2.031
	HSS(1)	-.151	.471	.103	1	.748	.860	.341	2.165
	FEO(1)	-.507	.495	1.048	1	.306	.603	.228	1.589
	ECE(1)	-.173	.506	.117	1	.733	.841	.312	2.268
	PAR(1)	-.002	.541	.000	1	.997	.998	.346	2.880
	Constant	.251	.502	.251	1	.616	1.286		
Step 2[a]	ECB(1)	.048	.456	.011	1	.917	1.049	.429	2.563
	MAC(1)	-.184	.449	.169	1	.681	.832	.345	2.006
	HSS(1)	-.151	.471	.103	1	.748	.860	.341	2.165
	FEO(1)	-.506	.490	1.067	1	.302	.603	.231	1.575
	ECE(1)	-.173	.506	.117	1	.733	.841	.312	2.266
	Constant	.251	.498	.254	1	.614	1.286		

Variables in the Equation (continued)

Step 3[a]	MAC(1)	-.175	.441	.158	1	.691	.839	.354	1.991
	HSS(1)	-.144	.466	.096	1	.757	.866	.347	2.160
	FEO(1)	-.500	.486	1.058	1	.304	.607	.234	1.573
	ECE(1)	-.169	.505	.113	1	.737	.844	.314	2.270
	Constant	.255	.497	.262	1	.609	1.290		
Step 4[a]	MAC(1)	-.183	.440	.173	1	.677	.833	.352	1.972
	FEO(1)	-.504	.486	1.079	1	.299	.604	.233	1.564
	ECE(1)	-.175	.504	.121	1	.728	.839	.313	2.252
	Constant	.158	.386	.167	1	.682	1.171		
Step 5[a]	MAC(1)	-.192	.439	.192	1	.661	.825	.349	1.949
	FEO(1)	-.510	.485	1.105	1	.293	.600	.232	1.554
	Constant	.126	.375	.114	1	.736	1.135		
Step 6[a]	FEO(1)	-.511	.485	1.111	1	.292	.600	.232	1.551
	Constant	.000	.239	.000	1	1.000	1.000		
Step 7[a]	Constant	-.128	.207	.382	1	.536	.880		

a. Variable(s) entered on step 1: ECB, MAC, HSS, FEO, ECE, PAR.

Model if Term Removed

Variable		Model Log Likelihood	Change in -2 Log Likelihood	df	Sig. of the Change
Step 1	ECB	-64.193	.011	1	.917
	MAC	-64.269	.164	1	.686
	HSS	-64.239	.103	1	.748
	FEO	-64.721	1.068	1	.301
	ECE	-64.246	.117	1	.732
	PAR	-64.187	.000	1	.997
Step 2	ECB	-64.193	.011	1	.917
	MAC	-64.272	.168	1	.681
	HSS	-64.239	.103	1	.748
	FEO	-64.731	1.088	1	.297
	ECE	-64.246	.117	1	.732
Step 3	MAC	-64.272	.158	1	.691
	HSS	-64.241	.096	1	.757
	FEO	-64.732	1.078	1	.299
	ECE	-64.249	.113	1	.737
Step 4	MAC	-64.327	.173	1	.677
	FEO	-64.791	1.100	1	.294
	ECE	-64.302	.122	1	.727
Step 5	MAC	-64.398	.192	1	.661
	FEO	-64.865	1.127	1	.288
Step 6	FEO	-64.964	1.133	1	.287

Variables not in the Equation

			Score	df	Sig.
Step 2[a]	Variables	PAR(1)	.000	1	.997
	Overall Statistics		.000	1	.997
Step 3[b]	Variables	ECB(1)	.011	1	.917
		PAR(1)	.000	1	.988
	Overall Statistics		.011	2	.995
Step 4[c]	Variables	ECB(1)	.004	1	.952
		HSS(1)	.096	1	.757
		PAR(1)	.000	1	.990
	Overall Statistics		.107	3	.991
Step 5[d]	Variables	ECB(1)	.001	1	.971
		HSS(1)	.104	1	.747
		ECE(1)	.121	1	.727
		PAR(1)	.000	1	.983
	Overall Statistics		.228	4	.994
Step 6[e]	Variables	ECB(1)	.003	1	.956
		MAC(1)	.193	1	.661
		HSS(1)	.122	1	.727
		ECE(1)	.141	1	.708
		PAR(1)	.004	1	.948
	Overall Statistics		.420	5	.995
Step 7[f]	Variables	ECB(1)	.037	1	.847
		MAC(1)	.198	1	.656
		HSS(1)	.147	1	.701
		FEO(1)	1.122	1	.290
		ECE(1)	.170	1	.680
		PAR(1)	.003	1	.956
	Overall Statistics		1.537	6	.957

a. Variable(s) removed on step 2: PAR.
b. Variable(s) removed on step 3: ECB.
c. Variable(s) removed on step 4: HSS.
d. Variable(s) removed on step 5: ECE.
e. Variable(s) removed on step 6: MAC.
f. Variable(s) removed on step 7: FEO.

Casewise List[a]

a. The casewise plot is not produced because no outliers were found.