BROWN UNIVERSITY

DOCTORAL THESIS

Applications of Decision Analysis in Alzheimer's Research

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A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy

in the

Department of Health Services, Policy and Practice

October 2024

This dissertation by Mauricio lopez Mendez is accepted in its present form by the Department of Health Services Research as satisfying the dissertation requirement for the degree of Doctor of Philosophy.

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Acknowledgements

I thank my dissertation chair, Dr. Thomas Trikalinos, for his invaluable lessons filled with contagious rigor and curiosity; it was an honor. I want to thank my advisor, Dr. Eric Jutkowitz, for the opportunity to work together and learn from him. I thank Dr. Omar Galarraga for his continuous support and feedback throughout my entire PhD journey. I thank Dr. Fernando Alarid-Escudero for almost a decade of invaluable mentoring, guidance, and engaging conversations. I also acknowledge Dr. Rowan Iskandar, for his early mentoring during my first year in the PhD.

I thank the Department of Health Services Research and Practice at Brown University for their continuous support, especially from their amazing staff. I thank the colleagues and friends I met along the way at Brown, it was a blessing to be in the same cohort as Drs. Bishnu Thapa, Catherine Ettman, Emma Tucher, Hace Oh, Kathryn Thompson, Nick Jones, and Sara Robertson.

Last but not least, I thank my wife (Isabel), my parents (Lucia and Victor), and my brother (Marco), who fill my life with joy and energy. Without them, this work could not have been done.

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Chapter 1

Introduction

Dementia affects 50 million people worldwide, leading to declines in cognitive and functional abilities, with many individuals also experiencing behavioral symptoms such as hallucinations and wandering (WHO, 2017). In the United States alone, more than 6 million Americans 65 and older are affected by dementia (Alz-Association, 2023). Long-term care for people living with dementia requires more care hours compared to those without dementia, imposing a significant strain on the health system, as well as on the families and caregivers of people living with dementia (Jutkowitz et al., 2020; Patterson et al., 2023; Li et al., 2024; Keeney et al., 2020; Hurd et al., 2013; MacNeil-Vroomen et al., 2020; Nandi et al., 2024).

Family caregivers are essential for providing care, as most people living with dementia reside in the community and receive substantial care within their homes (Friedman et al., 2015; NASEM, 2021a) . Through their ongoing support, family caregivers help to address the complex needs of those living with dementia and can support the effective incorporation of comprehensive approaches into care routines (NASEM, 2021b). At the same time, caregivers of people living with dementia often face significant burdens due to their caregiving responsibilities, such as stress, anxiety, depression, fatigue, and health problems due to demanding tasks, as well as social isolation (A Khalil et al., 2022; Shankar et al., 2014; Kristof et al., 2017) . Recognizing these diverse burdens has guided the incorporation of comprehensive support systems to assist caregivers in managing the multifaceted challenges they face.

Dyadic non-pharmacologic interventions typically provide support to people living with dementia via different mechanisms that can support their functional, behavioral, and cognitive abilities, as well as improve their quality of life and well being (NASEM, 2021a; Nickel, Barth, and Kolominsky-Rabas, 2018). In addition, dyadic non-pharmacologic interventions incorporate mechanisms through which caregivers can also receive support. For example, through tailored education and skills to ease care planning and monitoring, as well as counseling and other psychological supports (Nickel, Barth, and Kolominsky-Rabas, 2018; NASEM, 2023; NASEM, 2021b). Hence, non-pharmacologic interventions are crucial to provide comprehensive long-term care to people living with dementia. Studies involving randomized trials of non-pharmacologic psychosocial interventions for dyads have shown clinical and statistical improvements in outcomes for people living with dementia and their caregivers. Furthermore, evidence-informed studies have also shown that non-pharmacologic dementia-care interventions can be cost-effective (Jutkowitz et al., 2023; Gitlin et al., 2010a; Graff et al., 2008; Shaw et al., 2021; Vandepitte et al., 2020).

In order to prioritize the allocation of resources when planning the provision of care for current and future generations of people living with dementia, payers and decision makers must synthesize and analyze the benefits and costs associated with available treatments and interventions if they were made available to the general population living with dementia. For this task, decision analysis and decision-analytic tools are recommended, as they can provide a systematic account and analysis of the best available evidence on the etiology and progression of the disease, the relevant clinical and health-related outcomes, associated costs, and patient preferences (and ideally caregiver preferences). In other words, decision analysis is a means to identify the optimal set of acts (e.g., treatments, health technologies, screening strategies, non-pharmacologic interventions) that given the existing body of evidence are expected to yield the highest benefit (typically for society) at the lowest cost.

In this context, the present dissertation addresses two issues that arise in the decision analysis of non-pharmacologic interventions for people living with dementia. The first of these issues results from the incompatibility of the existing decision-analytic frameworks with the dyadic nature adopted by many non-pharmacologic interventions. Existing frameworks driven by decision analysis principles, such as cost-utility and cost-effectiveness analyses, are frequently conducted focusing either from the perspective of the patient or the caregiver. Consequently, decision makers often fail to account for the possible trade-offs and interdependence between preferences and health-related quality of life (HRQOL) of the person living with dementia and their caregiver, basing their allocation decisions on partial perspectives of the associated benefits and costs of interventions that support both members of the dyads.

In Chapter 2, we address this issue from a decision-theoretic point of view. We revise the foundational system of axioms of preferences and utilities and propose a novel approach to model collective preferences and utilities of members of a dyad that is consistent with the theoretical foundations of decision analysis and that allows evaluating decisions involving dyads. We formulate the assumptions required to construct this model and contrast its flexibility and generality with existing frameworks such as the spillover framework, which is the recommended approach to including benefits and indirect costs related to the caregiver in economic evaluations. Finally, we define and illustrate the steps and additional assumptions required to train this model from paired data on the preferences of people living with dementia and their caregivers.

In Chapter 3 we further extend this methodology and propose a new metric of dyadic health-related quality of life informed by real-world data. We used the Aging, Demographics, and Memory Study (ADAMS) (Langa et al., 2005) to identify people living with dementia and their caregivers and predict their individual HRQOL time trade-off-weights (TTO-weights). With the individual TTO-weights we estimate dyadic HRQOL TTO-weights using an Archimedean bivariate utility copula with a quadratic generating function. We also examine the association between predicted dyadic TTO-weights and dementia clinical features(functional and cognitive abilities, as well as behavioral symptoms) using adjusted linear regressions. The proposed dyadic HRQOL TTO-weights are a collective measure of HRQOL that incorporates the interdependence between HRQOL of people living with ADRD and their caregivers and can be used in economic evaluations of dyadic non-pharmacologic interventions.

The second issue that we address in this dissertation pertains to the analysis and evaluation of non-pharmacologic interventions that help people living with dementia to age safely at home. They are often referred to as transitional dementia-care interventions, since they are designed to support transitions between settings of care (e.g., discharge from the ER or hospital to the community), and often aim to extend time spent at home by reducing potentially avoidable transitions out of the community. The challenge in implementing and evaluating these interventions is that most people living with dementia would prefer to age at home and receive care within their communities (NASEM, 2024) but often experience disproportionately higher rates of falls, hospitalizations, emergency room visits, and mortality (Wysocki et al., 2014). To safely age at home, interventions must address a multiplicity of pathways through which a person living with dementia can end up receiving care outside of their communities. However, most transitional care interventions only address a specific path out of the community (e.g., reducing nursing home admissions) and evaluations of transitional care interventions often fail to account for competing adverse events that the person living with dementia can experience (NASEM, 2024).

In Chapter 4, we address this issue from a model-based decision-analytic framework. We develop a model that represents the dynamics of transition between different settings of care of a dementia diagnosed cohort of Medicare beneficiaries, including transitions into and out of inpatient care, emergency care, institutionalized long-term care (nursing homes and skilled nursing facilities), and home- and community-based care. We trained this model using a data repository that summarizes information from Medicare claims and nursing home minimum data set (MDS) assessments that provide the place and time at which health services were provided, including stays in non-Medicare-paid nursing homes (Intrator et al., 2011). In addition, we model the associated lifetime costs from Medicare's perspective to provide care to this population and across care settings, as well as the number of chronic health conditions that people living with dementia experience throughout their lifetime.

With this representation of the continuum of care, we evaluate the comparative effectiveness and cost-effectiveness of interventions that increase time in the community by reducing transitions from community to nursing home, 30-day ED readmissions or hospital readmissions, as well as composite strategies that reduce two or three transitions out of the community simultaneously. The treatment effects of interventions were extracted from published literature and modeled assuming proportional hazards over 18 months. Across interventions/strategies we compare average 30-day ER and hospital readmissions, NH admissions, length of stay (LoS) in the community, and total time gained in the community relative to standard of care. In cost-effectiveness analysis, we calculate ICERs as the incremental cost per year gained in the community and as the incremental cost per quality adjusted life year (QALY).

In summary, this dissertation addresses two main issues in decision analysis of non-pharmacologic interventions for dementia. The first issue is the incompatibility of existing decision-analytic frameworks with the dyadic nature of these interventions. A novel approach is proposed to model collective preferences and utilities of dyads, enhancing decision-making processes. The second issue pertains to evaluating interventions that help people with dementia age safely at home. A model-based decision-analytic framework is developed to assess the effectiveness and cost-effectiveness of such interventions, considering competing transitions between different care settings and the associated care costs. The proposed solutions constitute both methodological and applied advances in understanding the benefits and trade-offs derived from dyadic non-pharmacologic interventions and transitional care interventions, and emphasize the critical role of caregivers in providing care to people living with dementia, as well as the complex dynamics of transitions across settings of care that people living with dementia experience over their lifetime.

Chapter 2

Dyadic Decision Problems and Dyadic Valuation Functions

Abstract

Decision analysis over a set of healthcare interventions that affect two types of beneficiaries requires the correct assessment of joint preferences and health-related outcomes of beneficiaries. The spill-over framework allows to quantify potential benefits or harms that a caregiver experiences in response the benefits that healthcare interventions yield to patients. However, this framework does not consider the potential dependence between utilities and outcomes of patients and caregivers. This study develops a set of conditions under which a pair of interrelated beneficiaries (dyads) can collectively decide over a set of healthcare interventions that affect both. It proposes a dyadic ordinal preference function over deterministic consequences of intervention alternatives, as well as a dyadic Archimedean utility copula function over risky intervention alternatives. Furthermore, underlying assumptions are developed needed to estimate the dyadic Archimedean utility copula function from paired data on individual utility functions of dyad members and illustrate the flexibility that this general form offers in relation to other approaches. The dyadic Archimedean utility copula function can be used in the analysis of decisions that involve dyads and is flexible enough to capture interdependence between the individual utilities, as well as cases where the dyads do not exhibit attribute dominance. The possibility of estimating dyadic utility functions from paired utility data is an important advantage over existing frameworks.

2.1 Background

2.1.1 Motivation

In health services and medical contexts, decisions often involve consequences that affect more than one type of beneficiary. For example, mothers and their newborn (or still unborn) children may be affected by clinical decisions taken during pregnancy, childbirth, and/or in the postpartum period (Vlist et al., 2021). More generally, parent-child relations are a prototypical example of dyadic relations where it is convenient to think about the well-being of the dyad as a unit instead of or in addition to the individual well-being of the parent and the well-being of the child. Other prototypical examples in healthcare include patient-partner, patient-caregiver, and patient-doctor relations.

For the patient-caregiver relation, studies have quantified the health-related quality of life of patients living with Alzheimer's disease and Parkinson's disease (Moon et al., 2017; Lee et al., 2021), systemic lupus (Jolly et al., 2015), and end-stage renal disease (A Khalil et al., 2022), among others; and have included in their study design the evaluation of the quality of life of different types of caregivers (e.g. informal, family, non-family, etc.). In patient-partner settings, such as HIV-AIDS, studies have described intra-household dynamics that favor or deter infection, and interventions have been proposed to build and leverage strong support/caregiving systems within the household (Burton, Darbes, and Operario, 2010; Darbes et al., 2014; Karney et al., 2010). More dramatically, the SARS-CoV-2 pandemic uncovered the important role that the characteristics of intra-household relations can have on the determination of infection rates (e.g., the role of children in the spread of viral infection within a household), and highlighted the need to address prevention and resource prioritization strategies from perspectives that recognize the interaction, preferences, and outcomes of different individuals (Tseng et al., 2023) (Li et al., 2020).

Decisions involving pairs of beneficiaries, as in the aforementioned examples, often necessitate consideration of the consequences of decisions over their joint health-related outcomes. For example, improving the health-related quality of life of the patient may also improve the quality of life of the caregiver since they care and feel for the patient and/or because improving the patient's quality of life reduces the amount of care-giving hours they need, for example, by reducing or preserving the number of limitations in activities of daily living (ADLs). It is also possible that improving the health-related quality of life of the caregiver can have an additional benefit for the patient, since it can strengthen and improve their care-giving relationship and because the patient is also concerned for the caregiver, especially when the caregiver is a spouse or family member.

2.1.2 Standard Practice and Limitations

In psychology and human behavior studies, one of the main frameworks used to analyze the interrelation between members of different types of dyads is based on the actor-partner model (Cook and Kenny, 2005). This model acknowledges the interrelation between the different characteristics of the members of a dyad and how they interact to produce different types of dyad behavior.
In relation to care-giving partners, the Second Panel in Cost-Effectiveness Analysis in Health and Medicine recognized the critical importance of including the benefits and harms that a family member's illness has on the health of their caregivers (Neumann et al., 2016a). Specifically, the Second Panel recommends including benefits and indirect costs related to the caregiver in economic evaluations and health-technology assessments done from a societal perspective (Sanders et al., 2016).

For this purpose, the recommended framework relies on models of value that incorporate spillover effects. The theory behind spillover effects derives from consumer and welfare theory in economics (Mas-Colell, Whinston, Green, et al., 1995). Basu and Meltzer (2005) proposed that spillover effects can be incorporated into the analysis of economic choices made by a two-person household via inclusion of "altruistic" terms, also referred to as "Beckerian" terms (due to Gary Becker) (Basu and Meltzer, 2005; Becker, 1991).

The model from Basu and Meltzer is based on an intra-household model first proposed by Browning and Chiapori (Browning and Chiappori, 1998). In the case of a family of two (e.g.: a couple without children), this model captures spillovers by including the level of health and consumption of their respective partner or family member into their own individual utility functions. For persons a and b, cardinal utilities (interval scale)[1] of person a, $V^a()$, is a function of their own consumption (C^a) and own health (H^a), as well as consumption (C^b) and health (H^b) of person b. Likewise, the cardinal utility (absolute scale) of person b, $V^b()$, is a function of their own consumption and health (C^b) and (H^b), as well as the consumption and health of person a (C^a) and (H^a).

$$V^a\left(C^a(t), H^a(t), C^b(t), H^b(t)\right)$$

[1]This is not clear from the paper from Basu and Meltzer but it is implied since in the application of their model they derive and use quality of life weights which are interval scale numerical representations.

$$V^b(C^b(t), H^b(t), C^a(t), H^a(t))$$

A two-person household utility function $V^{a,b}()$ is then constructed as a weighted sum of the individual "altruistic" utility functions where a parameter γ ("distribution of power" parameter) is used to weight the individual utilities.

$$V^{a,b} = (1-\gamma)V^a(t) + \gamma V^b(t)$$

In the two-person household lifetime utility maximization problem, the objective function includes the products and cross-products of the marginal survival probabilities $S^a(t), S^b(t)$, as well as the "individualistic" utility function of the person a and b, that is, utility functions without altruistic terms: $U^a((C^a),(H^a))$ and $U^b((C^b),(H^b))$; and is solved subject to a budget constraint $M()$.

$$\begin{aligned} \underset{C^i(t),m_p^i(t)}{arg\ max} \sum_{t=0}^{T} \beta^t \Bigg(& \Big[S^a(t)S^b(t)\big((1-\gamma)V^a(t) + \gamma V^b(t)\big)\Big] \\ & + \Big[S^a(t)\big(1-S^b(t)\big)U^a(t)\Big] \\ & + \Big[\big(1-S^a(t)\big)S^b(t)U^b(t)\Big]\Bigg) \end{aligned} \tag{2.1}$$

where $\gamma \in [0,1]$, and is subject to the budget constraint:

$$M(S^a(t), S^b(t), C^a(t), C^b(t), m_i^a(t), m_i^b(t), I^a(t), I^b(t)) = 0$$

where $I^a(t), I^b(t)$ represent period-specific income levels, and $m_i^a(t) = (m_1^a(t), ..., m_k^a(t))$; $m_i^b(t) = (m_1^b(t), ..., m_k^b(t))$ represent the expenditures on k medical interventions at time period t.

Including altruistic terms allows to quantify for example the spill-over effect that a change in person a's health outcomes can have on the health utility of person b, and may be important for calculating the societal benefits of medical interventions or technologies; e.g., if spillovers are accounted for, cost-effectiveness conclusions may be altered.

However, there are important limitations and barriers in the application of this approach. First, data from the elicitation of utility functions that include altruistic terms, i.e. $V^a()$ and $V^b()$, are typically not available, and current approaches to obtain this evidence require a thorough assessment of the trade-offs that each person in the dyad is willing to incur with respect to their own well-being conditional on the other person's health status (e.g., worse health state of their partners). This approach can be costly and cognitively demanding for patients and their partners. Second, the spillover approach is typically not applied making the distinction between different types of beneficiaries and multi-objective interventions, i.e., does not acknowledge the possibility that an intervention may impact directly different types of beneficiaries, potentially through different mechanisms. Finally, the spillover model does not recognize the interrelation between the individual utility functions V^a and V^b. Since V^a and V^b are functions of individual consumption and health of both members, these two utility functions are potentially dependent since they share common arguments. However, by combining V^a and V^b as a weighted sum, this model implies utility independence between V^a and V^b. This means that from the household perspective, the utility of the patient is assessed independently of the caregiver's utility function, ignoring the potential association between their individual utilities.

These limitations are becoming more important given the recent increase in interventions that are explicitly designed to provide direct (and possibly indirect) health-related benefits to more than one type of beneficiary. An example of this are non-pharmacologic interventions targeting patients living with Alzheimer's Disease (AD) and Alzheimer's Disease and Related Dementias (AD/ADRD) and their caregivers, such as comprehensive care ADRD interventions (NASEM, 2022). In this sense, comprehensive care interventions recognize the importance of providing health services to care-giving partners and underscore the critical interrelation between patient and caregiver health-related outcomes.

However, existing methods and analysis frameworks lack the flexibility to accurately represent the value attributed to the collective benefits of dyadic interventions, and there is no guidance in the literature on how to integrate interdependence in health outcomes and preferences between members of a dyad. Therefore, it is necessary to revise the conceptualization of dyadic decision problems and the models of preferences used to capture the value of interventions and technologies that affect dyads.

In this chapter, I provide a framework for the specification of dyadic decision problems and propose a novel construction of a dyadic utility function that can address the current limitations of the spillover model.

2.2 Specification of a Dyadic Decision Problem

In this section, I pay special attention to the specification of elements that may require modification in the context of dyadic decision-problems: the decision-makers and beneficiaries, the set of acts, and the characteristics of valuation functions needed in a dyadic decision problem.

DECISION-MAKER(S): The decision-maker in a dyadic decision problem can be a single entity/person ($m = 1$) or a group ($m > 1$), where m is the number of decision-makers. The decision-maker(s) may be members of the dyad(s) themselves, but this is not required.

BENEFICIARIES: In dyadic medical decision problems, decisions pertain to two types of beneficiaries that are interrelated in some way relevant to the healthcare decision of interest. In this sense, the interrelated beneficiaries conform a structured entity, that I refer to as a "dyad". Likewise, interrelated beneficiaries may form a structured population, referred to as a "population of dyads". For example, in a clinical setting, a patient and their family caregiver can be considered a patient-caregiver dyad. In the health-policy context, policy-makers may consider a population of patient-caregiver dyads as the beneficiaries.

SET OF ACTS: The set of acts, ($\mathcal{A}$), can be finite or infinitely large and has to

- have at least two acts,
- and include the "do nothing" Act

$\mathcal{A}$ may include acts that impact both members of the dyad(s) directly and/or indirectly. For example, consider an act a and outcomes Y_1 and Y_2, indexed for each member of the dyad. In the first case, a affects Y_1 and Y_2 directly, e.g., a improves patient survival and provides direct support for care-giving duties through different mechanisms. In the second case, an act may impact directly one member (e.g. improve patient's mobility) and through that effect impact indirectly the other member (e.g. better patient mobility requires less care-giving hours). It is also possible to think of other acts that may have direct and indirect effects on both members of the dyad at the same time. These scenarios can also be constructed when thinking about a population of dyads in a health-policy setting.

Finally, here I assume that the marginal and joint (average) treatment effects of acts over $p-$dimensional outcomes have already been correctly identified from experimental and / or observational studies, or obtained from evidence synthesis and meta-analytic studies (Kennedy, Kangovi, and Mitra, 2019; Ding, Feller, and Miratrix, 2019).

VALUATION FUNCTIONS: A valuation function is a numerical representation of the preferences of decision-makers over elements of $\mathcal{A}$ or the consequences attached to those acts. In this sense, valuation functions returns a one-dimensional numerical value for each of the p-dimensional consequences attached to each act. Consider a finite set $\mathcal{C}$, where an element c of this set represents the p-dimensional consequences attached to a specific act $a \in \mathcal{A}$. I only consider valuation functions that are specified as scalar functions, i.e. that aggregate the p-dimensional consequences into a single dimension. I also consider that each element in $\mathcal{C}$ is decision-relevant for at least one member of the dyad.

We can distinguish between three types of valuation functions (Abbas, 2018a):

- *Preference functions ($P : \mathcal{C} \rightarrow \mathbb{N}$, or $P : \mathcal{C} \rightarrow \mathbb{R}$)*[2]: These functions represent a numerical rank over elements in $\mathcal{C}$. The ranks represent a weak order over the elements in $\mathcal{C}$. This ordinal representation is unique up to monotone transformations.

- *Value functions ($V : \mathcal{C} \rightarrow \mathbb{R}$)*: These functions return numerical values defined on an interval or absolute scale over elements in $\mathcal{C}$. In addition to representing a weak order over the elements in $\mathcal{C}$, the numerical representations on an interval or absolute scale allow for operations of distance or difference between two numerical values assigned to a pair of elements in $\mathcal{C}$, this difference is interpreted as the magnitude of the difference in preferences over the pair. If defined on an interval scale the numerical representation is unique up to linear transformations, while value functions defined on an absolute scale are unique up to identity transformations.

- *von Neumann-Morgenstern Utility functions ($U : \mathcal{C} \times \theta \rightarrow \mathbb{R}$)*: This numerical representation establish a weak order over combinations of elements in $\mathcal{C}$ and their respective (objective) probabilities of being realized. In this sense, the ordering pertains to lotteries of p-dimensional consequences attached to Acts, and the system of utilities not only considers the deterministic consequences of the Acts but also the risk of their realization as described by a known probability measure (θ) over the consequences attached to Acts. As shown by von Neumann-Morgenstern, the numerical representation of utilities is justified as long as the weak order over the expected utility of the consequences of Acts is accepted (Von Neumann and Morgenstern, 1947). In which case, numerical

[2] If only the ordering is important and the set of alternatives is finite, it should be enough to use the mapping into $\mathbb{N}$, however, it is also a valid and sometimes useful representation, e.g., countable sets of alternatives, to use a mapping into $\mathbb{R}$ with the understanding that the numerical representation is only meaningful at the ordinal level.

representation of the system of utilities is unique up to linear transformations (see Appendix A for the complete vNM axioms).

Compatibility of Valuation Functions: For compatibility, I require that the three valuation functions (Preference, Value, and Utility) represent the same system of ordinal preferences over consequences of Acts for a single individual. That is, if we obtained from the same individual a preference, value, and utility function over consequences attached to Acts, we must be able to obtain from either the utility or the value function, the same system of ordinal preferences as represented by the preference function. As an example, consider that we elicit from a single person utilities and values (in an absolute scale) over consequences $c = (c_1, c_2, c_3)$ attached to three Acts (a_1, a_2, a_3), respectively. Suppose that the preference function over the consequences represents the weak order $c_1 \succsim c_3 \succsim c_2$. If the three valuation functions of this person are compatible, then the rank transformation of the three utilities or the three values must yield the same ordering as the preference function or any strictly monotone transformation of the preferences over c_1, c_2, c_3 (i.e. yield strategically equivalent rankings):

$$Rank(U(c_1), U(c_2), U(c_3)) = g(P(c_1), P(c_2), P(c_3)) = Rank(V(c_1), V(c_2), V(c_3))$$

Where $Rank(.)$ is a function that returns the ranks over the set of utilities or values, and $g(.)$ is a strictly increasing transformation of the preference function over c.

2.3 Dyadic Additive Ordinal Preferences

In this section, I discuss the conditions under which a dyad can exhibit collective preferences. Consider a pair of individuals who must collectively choose elements of the set of acts $\mathcal{A}$. We can call this pair a "dyad". The acts in $\mathcal{A}$ have consequences that can directly or indirectly affect the well-being of both members of the dyad, jointly or separately.

A.1 WEAK ORDER[3] OVER CONSEQUENCES OF EACH MEMBER OF THE DYAD: The first assumption is that each member of the dyad can assert their own preferences over decision alternatives in $\mathcal{A}$, such that the preference relation, $\succsim$, is:

- **Complete:** each member can assert a complete weak order of preferences of decision alternatives. Consider all pairs of alternatives a and b, then under completeness, I can always assert a preference relation $\succsim$ between the elements of the pair, such that either alternative is preferred at least as the other, or I am indifferent between them.

$$a \succsim b \; or \; b \succsim a, \; or \; a \sim b$$

- **Transitive:** Consider triplets of decision alternatives a, b, c. Transitivity means that for all a, b, c, if I prefer a to b ($a \succsim b$), and b to c ($b \succsim c$), then by transitivity it must be that

[3] Also called a total preorder.

I also prefer a to c ($a \succsim$ c).

By assuming A.1 for each of the members in the dyad, then each member has a numerical representation of their own preferences over the consequences of the decision alternatives represented by the preference functions $P_1(\cdot)$ and $P_2(\cdot)$ (Mas-Colell, Whinston, Green, et al., 1995).[4] We can define the preference functions as mappings into $\mathbb{N}$, however it is customary in the health economics literature to represent ordinal preferences with functions that map into $\mathbb{R}$. To avoid discrepancies with existing literature, moving forward I will consider ordinal preference functions that map into $\mathbb{R}$.

$$P_1 : \mathcal{C} \to \mathbb{R}; \text{ s.t. } \quad a \succsim_1 b \implies P_1(a) \geq P_1(b)$$

$$P_2 : \mathcal{C} \to \mathbb{R}; \text{ s.t. } \quad a \succsim_2 b \implies P_2(a) \geq P_2(b)$$

where $\succsim_1$ denotes the preference relation from the perspective of member one, $\succsim_2$ denotes the preference relation from the perspective of member two, and $P_1(\cdot)$, $P_2(\cdot)$ denote the numerical representation of preferences of the first and second members of the dyad, respectively.

A.2 "ATTRIBUTE AWARENESS" OF MEMBERS OF THE DYAD: The next assumption that I require is "attribute awareness", which refers to the subsets of the attributes of the consequences of acts that are decision-relevant to each member of the dyad.

Consider two-dimensional consequences of acts that involve one attribute (Y_1) directly related to the well-being of the first member of the dyad (e.g. the health status of the first person in the dyad), and a second attribute (Y_2) that is directly related to the well- being of the second member. I consider three relevant (non-trivial) configurations of the individual preference functions depending on the "awareness" that each member exhibits over the attributes of the consequences:

- *symmetric awareness*: If both members of the dyad are "aware" of all the attributes of the consequences attached to acts in $\mathcal{A}$, then the individual preference functions of the members include both Y_1, and Y_2 as arguments; i.e., $P_1(Y_1, Y_2), P_2(Y_1, Y_2)$. This means that the ordering over two-dimensional consequences assigned by each member of the dyad will change as the levels of Y_1 or Y_2 change.

[4] Complete and transitive preferences guarantee that $P_1(\cdot)$ and $P_2(\cdot)$ exist such that if $a \succsim b$ for both members of the dyad, then $P_1(a) \geq P_1(b)$ for person one, and $P_2(a) \geq P_2(b)$ for person two, for any pair of alternatives $a, b \in \mathcal{A}$

- *asymmetric awareness*: If only one member of the dyad is "aware" of the attributes of the consequences, then only the individual preference function of the "aware" member must include both Y_1, and Y_2 as arguments; i.e., $P_1(Y_1, Y_2)$ and $P_2(Y_2)$ or $P_1(Y_1)$ and $P_2(Y_1, Y_2)$.

- *no awareness*: If none of the members of the dyad is aware of the full set of attributes of the consequences (i.e. the individualistic case), then their preference functions are uni-dimensional; i.e., $P_1(Y_1)$, $P_2(Y_2)$. This means that neither member considers the attributes that directly affect the well-being of the other member as decision-relevant.

If both members of the dyad have no awareness of the attributes, then it is most likely that the dyad will not be able to decide collectively on their own, unless the preferences of person 1 over Y_1 matches the preferences of person two over Y_2. In this case, the dyad will require the participation of an external agent to decide on behalf of them, such as the supra decision-maker (Keeney, Raiffa, and Meyer, 1993), or would require an agreement of concession between them such that one member of the dyad makes decisions on behalf of both of them. When each member of the dyad ranks consequences based on attributes that directly affects them, are also referred to as purely "individualistic" preferences, something assumed in the development of the impossibility theorem (Arrow, 1950).

Assessing Awareness: A simple test on each member of the dyad can confirm whether members of the dyad consider the attribute of the other member as decision relevant. Suppose consequences are described by levels of the pair (Y_1, Y_2). And for illustrative purposes, suppose that Y_1 is my own health status, and Y_2 is the health status of my partner. If I am not aware of my partner's health status as decision relevant, then my ordinal preferences over (Y_1, Y_2) must satisfy that I am indifferent between consequences that change my partner's health status but leave my own health status unchanged. This means that from the perspective of the first member, I am indifferent between a fixed level $Y_1 = y_1$ and all possible combinations of $Y_1 = y_1$ and any level of Y_2,i.e.:

$$(Y_1 = y_1, Y_2 = y_i) \sim_1 (Y_1 = y_1, Y_2 = y_j) \;\; \forall j$$

where $\sim_1$ denotes that the preference relation is from the perspective of the first member of the dyad. Likewise, from the perspective of the second member of the dyad, we have the following.

$$(Y_1 = y_i, Y_2 = y_2) \sim_2 (Y_1 = y_j, Y_2 = y_2) \;\; \forall j$$

In economics, the notion of "awareness" has also been described as "altruism" (Becker, 1991; Browning and Chiappori, 1998; Basu and Meltzer, 2005); in other contexts, like game theory, the inclusion of another player's "payoffs" into one's own preferences could be described as a "strategic" player (Von Neumann and Morgenstern, 1947; Nash, 1953).

For the remainder of the chapter I will only focus on the "symmetric awareness" case and will leave the development of a dyadic utility function under "asymmetric awareness" as a key avenue to be developed in the future. To be clear, asymmetric awareness might be very relevant in situations when one member of the dyad cannot formulate their own preferences; e.g., due to illness that affects their cognitive capacity; but in turn the other member is able to assert their own preferences over both attributes, but possibly with some error.

A.3 ORDERING AGREEMENT BETWEEN MEMBERS OF THE DYAD: Given A1- A2, I require that members of the dyad agree on the preference ordering of the two-attribute consequences. This means that $P_1(Y_1, Y_2)$ and $P_2(Y_1, Y_2)$ represent the same weak order over the two-attributes consequences, i.e., $\succsim_1 \equiv \succsim_2$.

For all consequences (Y_1, Y_2) and (Y_1', Y_2') and mappings $P_1(\cdot), P_2(\cdot)$

$$(Y_1, Y_2) \succsim (Y_1', Y_2') \implies P_1(Y_1, Y_2) \geq P1(Y_1', Y_2');\ P_2(Y_1, Y_2) \geq P_2(Y_1', Y_2')$$

Due to invariance to strictly increasing transformations of the numerical representations of ordinal preferences, the agreement between members of the dyad can be represented with identical preference functions P_1 and P_2 or strictly increasing transformations of each other. For a strictly increasing function $g(\cdot)$ and all consequences (Y_1, Y_2) and (Y_1', Y_2'), it can be shown that

$$P_1(Y_1, Y_2) \geq P1(Y_1', Y_2') \implies g(P_1(Y_1, Y_2)) \geq g(P1(Y_1', Y_2'))$$

hence, if we define $P_2(\cdot) := g(P_1(\cdot))$ [5]

$$P_1(Y_1, Y_2) \geq P1(Y_1', Y_2') \implies P_2(Y_1, Y_2) \geq P2(Y_1', Y_2')$$

Under ordinal agreement between members of the dyad, either $P_1(Y_1, Y_2)$ or $P_1(Y_1, Y_2)$ are equivalent representations of the same weak order over two-attribute consequences, and we can define the dyadic ordinal preference function as:

[5] The equivalent logic would apply if we defined $P_1(\cdot) := g(P_2(\cdot))$.

$$P_{Dyad}(Y_1, Y_1) := g(P_1(Y_1, Y_2)) \tag{2.2}$$

where $g(\cdot)$ is a strictly increasing function.[6]

A.4 ADDITIVE AND STRICTLY INCREASING PREFERENCES OVER CONSEQUENCES: The final assumption I require pertains to the functional form of ordinal preferences that each member has over the two-attribute consequences, and consequently of the dyad under ordinal agreement.

If a member of the dyad can think of their own preferences over each attribute of the consequences independently; in our example Y_1 and Y_2, then the preference function is said to be "separable" on each attribute, and can be specified as an additive preference function (Abbas, 2018a). In the dyadic case, we can again think of the symmetry of this assumption in relation to each of the members of the dyad and the different types of configurations depending on their compliance with this assumption. However, moving forward I will focus only on the case of "*symmetric additive preferences*", i.e., both members of the dyad have additive preference functions over two-attributes consequences.

Under symmetric additive preferences, the individual preference functions of each member of the dyad over two-attributes consequences have the following additive functional forms:

$$P_1(Y_1, Y_2) = f_{1,1}(Y_1) + f_{1,2}(Y_2)$$

$$P_2(Y_1, Y_2) = f_{2,1}(Y_1) + f_{2,2}(Y_2)$$

where $f_{1,1}(Y_1), f_{1,2}(Y_2)$ are strictly increasing functions of the first member of the dyad, and $f_{2,1}(Y_1), f_{2,2}(Y_2)$ are strictly increasing preference functions of the second member of the dyad, over attributes Y_1 and Y_2. Note that an additive structure does not imply that one-attribute functions $f_{1,1}(Y_1), f_{1,2}(Y_2), f_{2,1}(Y_1), f_{2,2}(Y_2)$ are strictly increasing, this preference structure is imposed for convenience down the road at a low-cost in certain situations. For example, if the two-attributes, Y_1, Y_2 are the individual health status of each member of the dyad, then the assumption that better health status for either member of the dyad is always preferred to less is not an unreasonable assumption for the dyad members, especially since they have to agree to

[6] If we defined $P_1(\cdot) := g(P_2(\cdot))$ instead, we can then define $P_{Dyad}(Y_1, Y_1) := g(P_2(Y_1, Y_2))$

the ordering of consequences of actions characterized by their individual health status. It is worth noting that a necessary and sufficient condition for additivity in the two-attribute case is that the ordering over consequences complies with the "double cancellation" property derived by Debreu (Debreu, 1960), this property can be verified eliciting preferences over a triplet of two-attribute consequences. (Appendix A)

A.4′ "AGREEMENT" UNDER ADDITIVE ORDINAL PREFERENCES: In **A.3**, I defined the equivalence between preference functions based on the invariance property to strictly increasing transformations. This was possible without saying anything about the functional form of P_1, P_2,and P_{Dyad}. Under **A4**, I have constrained the structure and nature of the representation of preference orderings that members of the dyad have over two-dimensional consequences, to a sum of one-attribute preferences. Imposing this functional form does not change our agreement condition in **A.3**, i.e., $\succsim_1 \equiv \succsim_2$, and the invariance property still holds since for all Y_1, Y_2, Y_1', Y_2'

$$
\begin{aligned}
& P_1(Y_1, Y_2) = f_{1,1}(Y_1) + f_{1,2}(Y_2) \geq P_1(Y_1', Y_2') = f_{1,1}(Y_1') + f_{1,2}(Y_2') \\
\implies \quad & g(P_1(Y_1, Y_2)) = g\Big(f_{1,1}(Y_1) + f_{1,2}(Y_2)\Big) \geq g(P_1(Y_1', Y_2')) = g\Big(f_{1,1}(Y_1') + f_{1,2}(Y_2')\Big)
\end{aligned}
$$

Consequently, we can define in the general form the dyadic preference function as follows:

$$P_{Dyad}(Y_1, Y_2) := m\Big(P_1(Y_1, Y_2)\Big) = m\Big(f_{1,1}(Y_1) + f_{1,2}(Y_2)\Big), \text{ or} \tag{2.3}$$

$$P_{Dyad}(Y_1, Y_2) := m\Big(P_2(Y_1, Y_2)\Big) = m\Big(f_{2,1}(Y_1) + f_{2,2}(Y_2)\Big) \tag{2.4}$$

where function $m(\cdot)$ is a strictly increasing function.

It is worth noting that under additive ordinal preferences it is possible to reason about the nature of the agreement between members of the dyad in a more intuitive way. The nature of the agreement between members of the dyad under additive ordinal preferences can be characterized based on the equivalent orderings expressed by the cross-terms $(f_{1,2}(Y_2), f_{2,1}(Y_1))$ and the non-cross-term $(f_{1,1}(Y_1), f_{2,1}(Y_1))$ in the preference functions of the members of the dyad.

First consider the preference function of member one of the dyad:

$$P_1(Y_1, Y_2) = f_{1,1}(Y_1) + f_{1,2}(Y_2)$$

The cross-term term $f_{1,2}(Y_2)$ denotes the preference function of member one over the attribute (Y_2) that is directly relevant to member two's well-being. Likewise, if we look at member two's preference function:

$$P_2(Y_1, Y_2) = f_{2,1}(Y_1) + f_{2,2}(Y_2)$$

The cross-term $f_{2,1}(Y_1)$ denotes the preferences function of the second member over the attribute (Y_1) which is directly related to the well-being of member one.

Recognizing the meaning of these cross-terms we can identify the source of agreement between each member's preferences by looking at the discrepancies between the cross terms, $f_{1,2}(Y_2)$ and $f_{2,1}(Y_1)$ with their corresponding non-cross-terms, $f_{2,2}(Y_2)$ and $f_{1,1}(Y_1)$, in the other member's preference function:

- **Mutual Agreement:** Under ordinal attribute preferences, we can formulate a stricter condition of agreement between members of the dyad such that $\succsim_1 \equiv \succsim_2$ over two-attribute consequences. The condition of agreement under additive ordinal preferences requires that each member of the dyad ranks each attribute in an equivalent way. i.e., for all Y_1, Y_1', Y_2, Y_2', $Y_1 \succsim_1 Y_1' \implies Y_1 \succsim_2 Y_1'$, and $Y_2 \succsim_1 Y_2' \implies Y_2 \succsim_2 Y_2'$. This condition is achieved if the dyadic members if the cross-terms in each of their individual preference functions yield equivalent orderings as the corresponding non-cross-terms, i.e.:

  $$g(f_{1,2}(Y_2)) = f_{2,2}(Y_2)$$

  and

  $$f_{2,1}(Y_1) = g(f_{1,1}(Y_1))$$

  where $g(\cdot)$ is applied in both cases and is a strictly increasing function that is also additive, i.e., $g(\cdot)$ is linear.[7]

If the transformation $g(\cdot)$ is the same function in both cases,[8] It can be shown

[7]This assumption restricts the form of the transformation $g(\dot{})$ to be linear, since we require that $g(f_{1,1}(Y_1) + f_{1,2}(Y_2)) = g(f_{1,1}(Y_1)) + g(f_{1,2}(Y_2))$. It can be shown that additive monotone functions have to be linear functions.

[8]This is a stricter condition than **A.3**, since it is required that $g(\cdot)$ is the same function transforming the one-attribute preference functions $f_{1,2}(Y_2), f_{1,1}(Y_1)$,to preserve the weak order over two-attribute consequences. Otherwise, distinct transformations between attribute dimensions can break the ties in the original (not transformed) rankings. For example, suppose $P_1(Y_1) = 1, P_1(Y_1') = 2, P_1(Y_1'') = 3$ and $P_2(Y_2) = 2, P_2(Y_2') = 1, P_2(Y_2'') = 1$, in additive form $P_1(Y_1, Y_2) = 1 + 2 = 3$, $P_1(Y_1', Y_2') = 2 + 1 = 3$, and $P_1(Y_1'', Y_2'') = 3 + 1 = 4$, where (Y_1'', Y_2'') is the most preferred consequence and $(Y_1, Y_2) \sim (Y_1', Y_2')$. Now suppose that I transform P_1 by scaling this function by a constant factor $c_1 = 2$, and transform p_2 by a scaling constant $c_2 = 10$, i.e., I use different strictly increasing transformations on the preference functions of each attribute. After transformation, the rankings of the two-attribute consequences in additive form yield $P_1(Y_1, Y_2) = 2 + 20 = 22$, $P_1(Y_1', Y_2') = 4 + 20 = 24$, and $P_1(Y_1'', Y_2'') = 6 + 10 = 64$, breaking the tie between (Y_1, Y_2) and (Y_1', Y_2').

that the weak order is preserved over the two-attribute consequences, thus complying with the agreement condition that $\succsim_1 \equiv \succsim_2$. This also means that the dyad can collectively decide on the basis of either of the individual preference functions, since for all Y_1, Y_1', Y_2, Y_2'

$$\begin{aligned} & f_{1,1}(Y_1) + f_{1,2}(Y_2) \geq f_{1,1}(Y_1') + f_{1,2}(Y_2') \\ \implies & g(f_{1,1}(Y_1)) + g(f_{1,2}(Y_2)) \geq g(f_{1,1}(Y_1')) + g(f_{1,2}(Y_2')) \end{aligned}$$

This can be expressed in the following definition.

$$P_{Dyad}(Y_1, Y_2) := h_1(Y_1) + h_2(Y_2) \tag{2.5}$$

where we defined the compositions $h_1 := (g \circ f_{1,1}); h_2 := (g \circ f_{1,2})$, function $g(\cdot)$ is a positive linear function, and $f_{1,1}(Y_1)$, $f_{1,2}(Y_2)$ are strictly increasing functions.[9] In the most general form, we can express the dyadic additive preference function as

$$P_{Dyad}(Y_1, Y_2) := m\Big(h_1(Y_1) + h_2(Y_2)\Big) \tag{2.6}$$

where $m(\cdot)$ is a strictly increasing function.

- **Partial or no Agreement over attributes of consequences:** It is possible that only one member of the dyad finds an agreement over the cross-term of their preference functions, e.g., $g(f_{1,2}(Y_2)) = f_{2,2}(Y_2)$ but $f_{2,1}(Y_1) \neq g(f_{1,1}(Y_1))$, or that they find no agreement at all. I do not consider these cases in this study.

In summary, the sets of conditions (**A.1:A.3** and **A.1:A.4'**) are necessary for a preference function $P_{Dyad}(Y_1, Y_2)$ to numerically represent the preference orderings of the dyad over two attribute consequences. These conditions essentially require that members of the dyad agree on how they think about their joint outcomes so that their preference functions represent equivalent preference relations over their joint outcomes. In the case of additive ordinal preferences, which I imposed in **A.4**, the agreement between members of the dyad can be assessed in a more intuitive way by analyzing the equivalence of the cross-terms of the preference functions of each member of the dyad, but it requires a stricter condition for one-attribute preferences to be equivalent. Both types of agreement (**A.3** and **A.4'**) are very strong assumptions since they require that $\succsim_1 \equiv \succsim_2$ over two-attribute consequences, and in many

[9]Note functions h_1, h_2 will also be strictly increasing functions since they are compositions of two strictly increasing functions.

situations this may not hold. Examples of partial or no agreement are easy to think of and have been studied extensively, e.g. players in zero-sum situations and bargaining problems may have adversarial preferences and restrictions over the set of decision alternatives for the dyad are necessary to find agreement. However, there are cases where mutual agreement can be a good representation of the joint preferences of the dyad. Consider again the example of two-attribute consequences describing levels of health status of each member of the dyad. If the members of the dyad care for each other's health status and if both members always prefer a better health status for both of them, the agreement condition is plausible and a model as defined in equations (2.3-2.6) would be a reasonable representation of their joint preferences.

2.4 An Archimedean Copula Representation of the Dyadic Utility Function

In the previous section, I developed the conditions needed to represent dyadic preferences over two-attribute consequences of decision alternatives and defined the dyadic preferences function (2.3) as an additive function with strictly increasing preferences over each attribute. In this section, I make explicit the connection between additive ordinal preference of the dyad and the construction of an Archimedean utility copula function to represent cardinal utilities over two-attribute consequences under risk. I start with a discussion of the von Neumann-Morgenstern representation of utilities and the conditions necessary for a numerical representation of dyadic utilities to exist under this representation.

VON NEUMANN-MORGENSTERN REPRESENTATION OF PREFERENCES OF THE DYAD: In the one-person case, utilities as defined by von Neumann and Morgenstern are numerical representations of preferences over decision alternatives under risk.

$$U : \mathcal{C} \times \Pi \to \mathbf{R}$$

where $\mathcal{C}$ is the set of consequences attached to decision alternatives, and Π is the set of probabilities of consequences in $\mathcal{C}$.

The collection of axioms that imply the existence of this representation encompasses assumptions of completeness and transitivity of preferences. By definition, a dyad with ordinal preferences denoted by $P_{Dyad}(Y_1, Y_2)$, as specified in equations (2.3-2.6), adheres to these two axioms.

Additionally, for a numerical representation of preferences under risk to exist, the representation of utilities of von Neuman and Morgenstern requires that the individual be capable of stating a preference relation between combinations of consequences of decision alternatives and their probabilities of realization, which we can call lotteries. Let $l \in \mathcal{L}$ be such a lottery and $\mathcal{L}$ be the set of all possible lotteries of elements of $\mathcal{C}$, including degenerate lotteries that express consequences that occur with probability $\pi = 1$.

To motivate this reasoning, consider three consequences a, b, c with strict ordering $a \succ b \succ c$. If we accept that the individual can state a preference, $\succsim$, between lotteries that involve the triplet a, b, c, we can gain more information about their preferences. In particular, the comparison between the prospect of obtaining b for sure (i.e., a degenerate lottery, l_b) and a lottery that yields consequence a with probability π, and consequence c with probability $1 - \pi$ (i.e., a lottery $l_{a,c}|_\pi$), provides additional information of the excess preference of b over c (abusing notation, I call this $e_{b,c}$) to the excess preference of a over c (call it $e_{a,c}$). Note that without knowing the magnitudes of $e_{b,c}$ and $e_{a,c}$, asserting our preference between these two lotteries provides the basis for a correspondence between the numerical value of $\pi \in [0, 1]$ and the notion of a ratio q of excess preferences.

Following this notion, the von Neumann-Morgenstern representation of utilities requires, in addition to a weak order over consequences, that an operation be given with the following properties:

For $a \succ b \succ c$, there exists a probability $\pi \in [0, 1]$ such that

$$\pi\, a + (1 - \pi) b \sim c$$

and that the operation is linear[10]:

$$U(\pi\, a + (1 - \pi) c) = \pi U(a) + (1 - \pi) U(c)$$

The axioms of continuity (not shown, see **3:B.a, 3:B.d** in (Von Neumann and Morgenstern, 1947)), guarantee that the numerical representation admits the operation of combining consequences with probabilities and that we can numerically compare

[10]A linear map is additive and homogeneous of degree 1, i.e., it does not matter whether you apply the linear operator before or after the operations of addition and scalar multiplication.

those combinations.

A.5 AGREEMENT ABOUT PREFERENCES OVER RISKY CONSEQUENCES: When we think about the utility representation of the preferences of the dyad, it is necessary to assume that members of the dyad have an agreement about their preferences over lotteries (a very strong assumption), such that for any value $\pi \in [0,1]$ and for any triplet a, b, c with strict order $a \succ b \succ c$

$$l_b \sim_1 l_{a,c}|_\pi \iff l_b \sim_2 l_{a,c}|_\pi$$

Since the von Neumann-Morgenstern numerical representation is unique up to positive affine transformations, we can define equivalent utility representations of members of the dyad in the following way:

$$U_2(Y_1, Y_2) := \phi(U_1(Y_1, Y_2)) = \alpha + \beta U_1(Y_1, Y_2)^{11} \tag{2.7}$$

where ϕ is a positive affine transformation, α, β are scalars, and $\beta > 0$. This assumption implies that the numerical representations of utilities of members of the dyad, U_1, U_2, correspond to the same system of preferences over consequences of acts and combinations of those consequences with probabilities, i.e., for all Y_1, Y_2, Y_1', Y_2'

$$U_1(Y_1, Y_2) > U_1(Y_1', Y_2') \implies \phi(U_1(Y_1, Y_2)) > \phi(U_1(Y_1', Y_2')),$$

and for any $\pi \in [0,1]$

$$\pi U_1(Y_1, Y_2) + (1-\pi) U_1(Y_1', Y_2') = U_1(Y_1'', Y_2'')$$
$$\implies \pi\phi\big(U_1(Y_1, Y_2)\big) + (1-\pi)\phi\big(U_1(Y_1', Y_2')\big) = \phi\big(U_1(Y_1'', Y_2'')\big)$$

To avoid confusion about this statement, it is important to discuss the implications of the uniqueness theorem of numerical representation of utilities under risk, as proved by von Neumann and Morgenstern. [12] The uniqueness theorem states that for any two (one-dimensional) mappings $u(b),\ u'(b)$ that preserve the weak order over the consequences of decision alternatives (i.e., $a \succsim b \implies u(a) \leq u(b)$, and $a \succsim b \implies u'(a) \leq u'(b)$, and are linear operators in the sense of $u\big((1-\pi)a + \pi b\big) = (1-\pi)u(a) + \pi u(b)$ and $u'\big((1-\pi)a + \pi b\big) = (1-\pi)u'(a) + \pi u'(b)$, for any $0 < \pi < 1$ and any a, b, there exists a unique mapping between $u(b)$ and $u'(b)$ of the form:

$$u'(b) = w_0 u(b) + w_1$$

[11] We could instead do the opposite and define $U_1(Y_1, Y_2) := \phi(U_2(Y_1, Y_2))$.

[12] See sketch of this proof in Appendix A and the complete proof in (Von Neumann and Morgenstern, 1947).

where $w_0,\ w_1$ are fixed scalars and $w_0 > 0$.
To prove this statement, von Neumann and Morgenstern show that we can choose a basis, i.e, a constrained mapping $h(b)$[13], that has the same properties as $u(b),\ u'(b)$, but is constrained in the sense that it is arbitrarily normalized to a certain range, e.g. $(0,1)$, such that we can express $u(b),\ u'(b)$ as positive affine transformations of $h()$, call these mappings $\phi_1 : h \to u$ and $\phi_2 : h \to u'$, and their inverses ϕ_1^{-1} , ϕ_2^{-1}, respectively. From these equivalences, the transformation $u'(b) = w_0 u(b) + w_1$ is trivially derived.[14]

The implication of this theorem is that any two numerical representations of the same preferences of consequences of alternatives and combinations of those consequences with their probabilities can be related via a positive affine transformation; $\phi : u \to u'$, such that $u'(b) = \phi(u(b)) = w_0 u(b) + w_1$.

At the same time, this theorem implies that if an arbitrary scale is chosen, e.g., $(0,1)$, mappings from $u(b),\ u'(b)$ to a representation normalized to this scale, e.g., $h()$, exist and that $u(b),\ u'(b)$ must be identical in this arbitrary scale. To see this, observe that we can apply the inverse transformations ϕ_1^{-1} , ϕ_2^{-1} to $u(b),\ u'(b)$, respectively, which implies

$$\phi_1^{-1}(u(b)) = h(b) = \phi_2^{-1}(u'(b))$$[15]

The implications of this theorem in defining the uniqueness of the dyadic utility function can be thought of in the same way

$$U_2(Y_1,Y_2) = \phi(U_1(Y_1,Y_2)) \implies \phi_2^{-1}(U_2(Y_1,Y_2)) = H(Y_1,Y_2) = \phi_1^{-1}(U_1(Y_1,Y_2))$$

for any Y_1, Y_2, where ϕ is a positive affine transformation, and $H(Y_1,Y_2)$ is a numerical representation normalized to an arbitrary scale. Moving forward, I will assume that members of the dyad have identical utility representations over a set of consequences of acts and combinations of those acts with probabilities after transformation to the same arbitrary scale $(0,1)$.[16]

[13]The existence of such a function and uniqueness are proven in the Appendix of (Von Neumann and Morgenstern, 1947), Lemmas **A:R** and **A:S**.
[14]See Appendix A.
[15]More detail is given in Appendix A.
[16]If it is the case that $U_1(Y_1,Y_2), U_2(Y_1,Y_2)$ are in different scales but otherwise comply with $U_2(Y_1,Y_2) = \phi(U_1(Y_1,Y_2))$, we only need to find $\phi_1, \phi_2, \phi_1^{-1}, \phi_2^{-1}$ to map $U_1(Y_1,Y_2), U_2(Y_1,Y_2)$ to $H(Y_1Y_2) \in (0,1)$.

A DYADIC ARCHIMEDEAN UTILITY COPULA: Archimedean utility copulas are the general class of multi-attribute utility functions[17] that correspond to additive ordinal preferences and are strictly increasing with each argument at the maximum value of the complement attribute (Abbas and Sun, 2015a). Multiattribute utility functions and utility copula representations are defined in Appendix A.

From Section 2.3, recall that assumptions **A.1:A.4′** imply that preferences over two-attribute consequences of members of the dyad are equivalent, i.e., $\succsim_1 \equiv \succsim_2$. Consequently, a common preference function can numerically represent the preferences of the dyad over consequences of acts that affect them both, that is

$$P^{ma}_{Dyad}(Y_1, Y_2) = m\Big(h_1(Y_1) + h_2(Y_2)\Big)$$

as defined in equation (2.6).

In this subsection, I develop the additional conditions necessary to represent dyadic preferences under risk as an Archimedean utility copula. The derivation of an Archimedean utility copula starting from an additive preference function can be consulted in Abbas and Sun (2015).

Assuming agreement on preferences over risky consequences **A.5**, we can now formulate the dyadic utility function as an Archimedean utility copula function $U_{Dyad}(Y_1, Y_2)$ of the form:

$$\begin{aligned} U_{Dyad}(Y_1, Y_2) &= C\big(U_{Dyad}(Y_1, max(Y_2)), U_{Dyad}(max(Y_1), Y_2)\big) \\ &= \psi^{-1}\Big[\psi\big(U_{Dyad}(Y_1, max(Y_2))\big)\psi\big(U_{Dyad}(max(Y_1), Y_2)\big)\Big] \end{aligned} \tag{2.8}$$

where:

- C is a copula function $C : [0,1]^2 \to [0,1]$, that is continuous, non-decreasing, normalized such that $C(0,0) = 0$ and $C(1,1) = 1$, and satisfies the property of positive linear transformation at a reference value of the complement attribute (see Appendix A).
- $\psi(\cdot)$ is the generating function, a non-negative, continuous and strictly increasing function on $[0,1]$, when normalized, $\psi(1) = 1$;
- $U_{Dyad}(Y_1, max(Y_2))$ is the upper boundary two-attribute utility function over attribute Y_1 that directly affects member one's well-being while setting the

[17] Utilities as defined by von Neumann and Morgenstern.

other attribute Y_2 that affects member two at its most preferred level, i.e., $max(Y_2)$.

- $U_{Dyad}(Y_2, max(Y_1))$ is the upper boundary two-attribute utility function over attribute Y_2 that directly affects of member two's well-being while setting the other attribute Y_1 that affects member one at its most preferred level, i.e., $max(Y_1)$.

GENERATING FUNCTION: Under mutual utility independence, the generator function will be the identity function, however in any other case, the generator will have a different form.[18] In the case of utility dependence we must determine the form of $\psi(\dot{)}$ and fit data to its parameter(s). As shown in Abbas and Sun (2019a), a polynomial generator provides an approximation that is guaranteed to match the corner values[19] of the utility surface and will get closer to the true solution as its power increases. Moving forward, I will illustrate the construction of the dyadic utility copula using a one-parameter polynomial generator as an example, the quadratic generating function $\rho_\alpha(t)$ of the form:

$$\rho_\alpha(t) = (1+\alpha)t - \alpha t^2, \quad \text{where} -1 \leq \alpha \leq 1$$

It will be convenient for estimation to use a normalized quadratic generator. First, define the function $\psi(t) = k\ \rho_\alpha(t) + (1-k)$, where the constant k is determined according to **Equation 12** in Abbas and Sun (2019a) and must comply with $k = 1 - \psi(0)$. Rearranging, we obtain an expression for the quadratic generator $\rho^*(t)$ in terms of t and k as:

$$\begin{aligned}\rho^*(t) &= \frac{\psi(t) - (1-k)}{k} \\ &= \frac{1}{k}\psi(t) + 1 - (\frac{1}{k})\end{aligned}$$

Substituting $\rho_\alpha(t)$ into $\psi(t)$, we obtain the normalized version of the quadratic generating function as:

$$\rho^*_\alpha(t) = \frac{1}{k}\Big(k((1+\alpha)t - \alpha(t^2)) + (1-k)\Big) + 1 - (\frac{1}{k})$$

we can verify that it is normalized since $\rho^*_\alpha(t=0) = 0$; $\rho^*_\alpha(t=1) = 1$. The inverse of the normalized generator is expressed as:

[18] A definition of utility independence is provided in Section 2.5. and in Appendix A.
[19] Defined in the next section where I delineate steps for estimation of the copula model.

$$\rho_{\alpha}^{-1}(s) = \begin{cases} s, & \text{if } \alpha = 0. \\ \frac{\alpha+1-\sqrt{(1+\alpha)^2-4\,\alpha\, s}}{2\,\alpha}, & \text{otherwise.} \end{cases}$$

Finally, the dyadic Archimedean utility copula with a normalized quadratic generating function has the form:

$$\begin{aligned} U_{Dyad}(Y_1, Y_2) &= \rho_{\alpha}^{-1}\left[\rho_{\alpha}^{*}(U_{Dyad}(Y_1, max(Y_2)))\rho_{\alpha}^{*}(U_{Dyad}(max(Y_1), Y_2))\right] \\ &= \frac{(\alpha+1) - \sqrt{(1+\alpha)^2 - 4\alpha\left(\frac{1}{k}\left\{\prod_{\substack{i,j\in(1,2)\\ i\neq j}}(k[(1+\alpha)U_{Y_i,max(Y_j)} - (\alpha U_{Y_i,max(Y_j)})^2] + (1-k))\right\} + 1 - \frac{1}{k}\right)}}{2\alpha} \end{aligned} \tag{2.9}$$

where for a more compact notation I adopt $U_{Y_1,max(Y_2)}$ and $U_{max(Y_1),Y_2}$ to denote the boundary dyadic utility functions $U_{Dyad}(Y_1, max(Y_2))$, $U_{Dyad}(max(Y_2), Y_2)$, respectively.

A.5' INTERCHANGEABILITY AT THE BOUNDARIES: Note that the above construction, as defined in equations (2.8) and (2.9), uses the dyadic boundary utilities as inputs, $U_{Y_1,max(Y_2)}$ and $U_{max(Y_1),Y_2}$, however these functions are not directly observed from the paired data since they represent the collective utility function of the dyad. Similarly to what I pointed out as a limitation in the 2-person household utility function from Basu and Meltzer, these functions are rarely elicited and a thorough empirical characterization can be costly and cognitively demanding for members of the dyad.

The multi-attribute utility copula formulation offers an alternative to characterize empirically the dyadic utility function using paired data on the individual utility function of each member of the dyad. However, this necessitates the strong assumption that I postulate in **A.5**, in which I essentially assume that members of the dyad have the same preferences over two-attribute consequences and their combination with probabilities. If we accept this assumption, we can express the boundary dyadic utility functions $U_{Dyad}(Y_1, max(Y_2))$, $U_{Dyad}(max(Y_1), Y_2)$ in terms of the individual boundary utility functions of each member of the dyad, e.g. $U_1(Y_1, max(Y_2)$, $U_2(max(Y_1), Y_2))$, which are observable from paired data. The individual boundary utility functions for each member of the dyad are denoted below.

- $U_1(Y_1, max(Y_2))$ and $U_1(max(Y_1), Y_2)$ for member one; and
- $U_2(Y_1, max(Y_2))$ and $U_2(max(Y_1), Y_2)$ for member two.

Due to invariance of utility representations under **A.5** we can define the boundary utility functions of a member of a dyad as positive affine transformations of the boundary utility functions of the other member. The restriction again is that the the transformation ϕ must be the same transformation in both cases.

Under assumption **A.5**, we define

$$U_2(Y_1, Y_2) := \phi(U_1(Y_1, Y_2)) = \alpha + \beta U_1(Y_1, Y_2)$$

and we can also define

$$\begin{aligned} U_2(Y_1, max(Y_2)) &:= \phi(U_1(Y_1, max(Y_2))) = \alpha + \beta U_1(Y_1, max(Y_2)); \\ U_2(max(Y_1), Y_2) &:= \phi(U_1(max(Y_1), Y_2)) = \alpha + \beta U_1(max(Y_1), Y_2) \end{aligned} \tag{2.10}$$

where α, β are scalars, and $\beta > 0$.

Consequently, under **A.5**, we can equate the dyadic boundary utility functions with a linear transformation ϕ of the individual boundary functions of members of the dyad, [20] i.e.:

$$\begin{aligned} U_{Dyad}(Y_1, max(Y_2)) &= U_2(Y_1, max(Y_2)) = \alpha + \beta U_1(Y_1, max(Y_2)) \\ U_{Dyad}(max(Y_1), Y_2) &= U_2(max(Y_1), Y_2) = \alpha + \beta U_1(max(Y_1), Y_2) \end{aligned} \tag{2.11}$$

where α, β are scalars, and $\beta > 0$.

Note that by defining $U_2(Y_1, max(Y_2)) := \phi(U_1(Y_1, max(Y_2)))$ and $U_2(max(Y_1), Y_2) := \phi(U_1(max(Y_1), Y_2))$ I am anchoring the dyadic utility function to the scale of $U_2(\cdot)$ [21]. If $U_1(\cdot)$ and $U_2(\cdot)$ are not scaled satisfactorily, we can choose an arbitrary scale, e.g., $(0, 1)$, and transform $U_1(\cdot)$ and $U_2(\cdot)$ through ϕ_1^{-1} and ϕ_2^{-1}, in which case $U_1(\cdot)$ and $U_2(\cdot)$ will become identical, as illustrated in **A.5**.

Moving forward, we adopt the normalization of both $U_1(\cdot)$ and $U_2(\cdot)$ to the scale $(0, 1)$, and thus should be considered identical, i.e., $U_1(Y_1, Y_2) = U_2(Y_1, Y_2)$. Consequently, $U_1(Y_1, max(Y_2))$ and $U_2(Y_1, max(Y_2))$ can be used interchangeably, as well as $U_1(max(Y_1), Y_2)$ and $U_2(max(Y_1), Y_2)$. Hence, under normalization to a common scale, we have

[20] There is no additional assumption here, since $U_2(Y_1, Y_2) = \phi(U_1(Y_1, Y_2)) \implies U_2(Y_1, max(Y_2)) = \phi(U_1(Y_1, max(Y_2)))$ and $U_2(max(Y_1), Y_2) = \phi(U_1(max(Y_1), Y_2))$.

[21] The opposite could be done, if we defined $U_1(Y_1, max(Y_2)) := \phi(U_2(Y_1, max(Y_2)))$ and $U_1(max(Y_1), Y_2) := \phi(U_2(max(Y_1), Y_2))$, instead.

$$\begin{aligned} U_{Dyad}(Y_1, max(Y_2)) &= U_2(Y_1, max(Y_2)) = U_1(Y_1, max(Y_2)) \\ U_{Dyad}(max(Y_1), Y_2) &= U_2(max(Y_1), Y_2) = U_1(max(Y_1), Y_2) \end{aligned} \tag{2.12}$$

Finally, if we accept that **A.5** holds, and under appropriate normalization, we can express the dyadic utility as a function of the individual boundary utility functions $U_1(Y_1, max(Y_2))$ and $U_2(max(Y_1), Y_2)$:

$$\begin{aligned} U_{Dyad}(Y_1, Y_2) &= C\big((U_1(Y_1, max(Y_2))), (U_2(max(Y_1), Y_2))\big) \\ &= \psi^{-1}\Big[\psi\big((U_1(Y_1, max(Y_2)))\big)\psi\big((U_2(max(Y_1), Y_2))\big)\Big] \end{aligned} \tag{2.13}$$

Assumption **A.5** is important conceptually and also in practice, because in Section 2.3 I established mutual agreement conditions that guarantee that each person provides equivalent rankings over the attributes; however, the vNM utility representations also provide information about preference over risky consequences. Otherwise, the members of the dyad can have agreement over the ordinal rankings of consequences but disagreement over their preferences between risky consequences. Furthermore, identifying the dyadic utility function in terms of individual boundary utility functions of members of the dyad, under **A.5**, and the copula function allows us to characterize the dyadic utility empirically from paired data and potentially reduce the cost and burden of elicitation. This step is presented in the next section of this chapter, where I provide guidance on how to fit a dyadic Archimedean utility copula from paired data.

2.5 Estimation of $U_{Dyad}()$ from paired data:

Having identified the dyadic Archimedean utility copula as a function of the individual upper boundary utilities under the very strict assumption of interchangeability at the boundaries, I turn to describe the steps necessary to estimate an Archimedean utility copula from data on the paired utilities of a homogeneous population of dyads. By "homogeneous," I mean that the dyads are assumed to be representative of an archetypical profile of preferences over consequences.

Archimedean utility copulas relax attribute dominance (AD) and mutual utility independence (MUI); I provide a brief description of these assumptions below, but encourage the reader to refer to the original sources in citation for a complete exposition of these concepts.

- ATTRIBUTE DOMINANCE (Abbas and Howard, 2005): For utility functions that are also strictly increasing with each attribute except at the minimum boundary values $U(Y_1, min(Y_2))$ and $U(min(Y_1), Y_2)$, the attribute dominance assumption means that if either Y_1 or Y_2 are at their minimum values, the two-attribute utility function is zero. We can express this via the 2-attribute utility function as: $U(min(Y_1), Y_2) = U(Y_1, min(Y_2)) = 0$. (see Appendix A)

- MUTUAL UTILITY INDEPENDENCE (Keeney, Raiffa, and Meyer, 1993): If one attribute Y_1 is utility-independent of another attribute Y_2, the decision-maker can declare preferences over lotteries that involve attribute Y_1 without consideration of the level of attribute Y_2. This also means that the value of the conditional preferences over Lotteries of Y_1 conditional on a reference value of Y_2, e.g., $max(Y_2)$, does not change as we vary the reference value of Y_2, i.e, for a given realization of $Y_1 = y_1$, the conditional utilities are equivalent regardless of which reference value we condition on $U(Y_1 = y_1 \mid max(Y_2))) = U(Y_1 = y_1 \mid min(Y_2))$. Mutual utility-independence is the special case when Y_1 is utility independent of Y_2 and Y_2 is also utility independent of Y_1. This means that the decision-maker can declare preferences over lotteries that involve attribute Y_1 without consideration of the level of attribute Y_2 and vice-versa. (Appendix A)

Depending on which set of assumptions we are working with, we will require different estimation targets. The next subsections explain how under these assumptions the estimation from data is simplified and propose alternatives for estimation when these assumptions are relaxed. First, I describe the process of estimating the upper boundary utility curves from paired data, secondly I discuss the difficulties of estimating corner values of the dyadic utility function, and finally, I propose alternatives for estimating the parameters of the polynomial generating function.

2.5.1 Estimation of Upper Boundary Utilities:

Since all preference profiles (based on AD and MUI) require the estimation of the upper boundary utilities, I first describe potential approaches to estimate these functions from paired data of the outcomes and the associated upper boundary utilities of the dyads.

The upper boundary utility functions of a two-attribute Archimedean utility copula can be represented in terms of conditional utility functions and the corner values (Abbas, 2018a). This is possible due to the definition of conditional utility which establishes the following equivalences:

$$U_1(Y_1 \mid max(Y_2)) = \frac{U_1(Y_1, max(Y_2)) - U_1(min(Y_1), max(Y_2))}{U_1(max(Y_1), max(Y_2)) - U_1(min(Y_1), max(Y_2))} \tag{2.14}$$

$$U_2(Y_2 \mid max(Y_1)) = \frac{U_2(max(Y_1), Y_2) - U_2(max(Y_1), min(Y_2))}{U_2(max(Y_1), max(Y_2)) - U_2(max(Y_1), min(Y_2))} \tag{2.15}$$

The definition relates the upper boundary utility curves and the conditional utility curves when one of the attributes is set at its maximum value. This is convenient because the conditional utility curves at the upper boundaries are directly observable from paired data.

Upper Boundary Curves under Attribute Dominance:

When the two-attribute utility function is an attribute dominance utility function, then we can estimate the upper boundary utility functions using only the observed conditional utilities of each member of the dyad when the other member is set at its maximum (at the upper boundary). If the attribute dominance dyadic utility function is normalized to a range $[0, 1]$, the terms:

$$U_1(min(Y_1), max(Y_2)) = 0; \;\; U_1(max(Y_1), max(Y_2)) = 1$$

and equation (2.14) simplifies to:

$$U_1(Y_1 \mid max(Y_2)) = U_1(Y_1, max(Y_2)) \tag{2.16}$$

Likewise, under AD, since the terms:

$$U_2(max(Y_1), min(Y_2)) = 0; \;\; U_1(max(Y_1), max(Y_2)) = 1,$$

equation (2.15) simplifies to:

$$U_2(Y_2 \mid max(Y_1)) = U_2(max(Y_1), Y_2) \tag{2.17}$$

This result facilitates estimation considerably in the attribute dominance case, since we only need to estimate $U_1(Y_1 \mid max(Y_2))$ and $U_2(Y_2 \mid max(Y_1))$, which can be done from the paired data directly by conditioning on the other member's attribute at its maximum. Below I illustrate parametric and non-parametric approaches for doing so.

- **Parametric estimation of upper boundary curves:** In general, the parametric models must be constrained to families of strictly increasing functions. As an example, suppose that we have good domain knowledge of the decision problem and the preferences of members of the dyad and we know that the underlying true preferences follow exponential functions. Then, we can fit the paired data to the parameters of the exponential boundary curves θ_1, θ_2.

The estimation approach I adopt here is via nonlinear least squares in which we have nonlinear functions $U_1(Y_1 \mid max(Y_2))$ and $U_2(Y_1 \mid max(Y_2))$, and the optimization problem consists of minimizing the sum of squared residuals subject to the constraint on θ_1 or θ_2.Let $U_{1,i}^{UB}$ denote the i^{th} observation of conditional utilities of member one when setting member two's utility at its upper boundary. Similarly, $U_{2,i}^{UB}$ denotes the i^{th} observation of conditional utilities of member two when setting member one's utility at its upper boundary, then the two optimization problems we need to solve are:

$$\underset{\theta_1 \in \Theta}{arg\ min} \Big[\sum_i^n L\big(U_{1,i}^{UB}, f(Y_1, \theta_1)\big) \Big] \tag{2.18}$$

and

$$\underset{\theta_2 \in \Theta}{arg\ min} \Big[\sum_i^n L\big(U_{2,i}^{UB}, f(Y_2, \theta_2)\big) \Big] \tag{2.19}$$

where $L\big(U_i^{UB}, f(Y_i, \theta_i)\big)\big)$ is a loss function, $f(Y_i, \theta_i)\big)$ are the predictions of the parametric models, and Θ is the space of possible parameter values. In our example, $f(Y_1, \theta_1) = 1 - exp^{-\theta_1 Y_{1,i}}$, $f(Y_2, \theta_2) = 1 - exp^{-\theta_2 Y_{2,i}}$, $\Theta \subseteq \mathbb{R}^+$, and $L\big(U_i^{UB}, f(Y_i, \theta_i)\big)$ is a quadratic loss function.

- **Non-parametric estimation of upper boundary curves:** As exploratory or as a final model; monotonically constrained smoothing splines are another approach for approximating the two upper boundary utility functions. Here I follow the monotone smoothing spline approach, where in the objective function a penalty term is included and is parameterized with a "smoothness" parameter λ. This type of optimization problems are often referred to as "regularization problems". In our example, if we follow this approach we would in general try to solve the minimization problems :

$$\underset{f \in \mathcal{H}}{arg\ min} \Big[\sum_i^n L\big(U_{1,i}^{UB}, f(Y_1)\big) + \lambda J(f) \Big] \tag{2.20}$$

and

$$\underset{f \in \mathcal{H}}{arg\ min} \left[\sum_{i}^{n} L\big(U_{2,i}^{UB}, f(Y_2)\big) + \lambda J(f) \right] \tag{2.21}$$

where $L\big(U_i^{UB}, f(Y_i)\big)$ is a loss function (for example, quadratic loss is used in the parametric approach above), $J(f)$ is a penalty functional and $\mathcal{H}$ is a space of functions on which $J(f)$ is defined (Hastie, Tibshirani, and Friedman, 2009). For details on the specification of $f(Y)$, and the penalty on the first and second derivatives of $f()$ (through $J(f)$) to guarantee a monotonically increasing function, it is recommended to consult Ramsay 1998 (Ramsay, 1998a). Finally, the "smoothing" parameter λ can be determined via cross-validation by appropriately splitting the data into "training" and "test" subsets.

Upper Boundary Curves under No Attribute Dominance:

When the dyadic utility function does not exhibit attribute dominance, we require knowledge of the corner values of the utility surface to obtain the complete upper boundary curves, in addition to the conditional utility functions at the upper boundaries. From the definition of conditional utility, we see that without attribute dominance, equations (2.14) and (2.15) do not simplify, and the upper boundary utility functions are linear combinations of the conditional utility functions multiplied by scalar coefficients that are functions of the corresponding corner values:

$$\begin{aligned} U_1(Y_1, max(Y_2)) &= U_1(min(Y_1), max(Y_2)) \\ &\quad + \big(1 - U_1(min(Y_1), max(Y_2))\big) * U_1(Y_1 \mid max(Y_2)) \\ &= k_{1,Y_2} + (1 - k_{1,Y_2}) * U_1(Y_1 \mid max(Y_2)) \end{aligned} \tag{2.22}$$

and

$$\begin{aligned} U_2(max(Y_1), Y_2) &= U_2(max(Y_1), min(Y_2)) \\ &\quad + \big(1 - U_2(max(Y_1), min(Y_2))\big) * U_2(Y_2 \mid max(Y_1)) \\ &= k_{2,Y_1} + (1 - k_{2,Y_1}) * U_2(Y_2 \mid max(Y_1)) \end{aligned} \tag{2.23}$$

Where $k_{1,Y_2} = U_1(min(Y_1), max(Y_2))$ is the corner value at the upper boundary of member's two health status; $k_{2,Y_1} = U_2(max(Y_1), min(Y_2))$ is the corner value at the upper boundary of member's one health status. To preserve strictly increasing upper boundary functions, k_{1,Y_2},$k_{2,Y_1} \in [0,1)$.

Unlike the upper boundary conditional utility functions, corner values are not directly observed from paired data. I propose two ways to approximate the corner values k_{1,Y_2}, k_{2,Y_1}, the first approach relies on direct elicitation of the corner values, and the second approach relies on the paired data of the dyads or expert opinion.

- *Direct elicitation of corner values:*

  Under the conditions of interchangeability of the upper boundary utilities, we can assess the corner values by eliciting one utility assessment from each member of the dyad. Utility assessments must be designed to obtain from each member of the dyad the indifference probability p of obtaining for certain the two-dimensional consequence $(min(Y_1), max(Y_2))$ for member one or $(max(Y_1), min(Y_2))$ for member two, or entering a lottery that yields with probability p the most preferred two-dimensional consequence $(max(Y_1), max(Y_2))$ or the least preferred consequence $(min(Y_1), min(Y_2))$ with probability $(1 - p)$. This is illustrated in the indifference assessments shown in Figures 2.1 and 2.2:

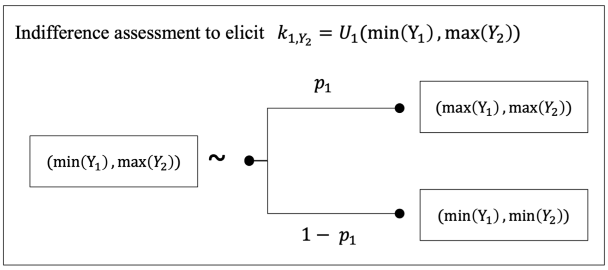


FIGURE 2.1: Indifference assessment Corner Value from member one

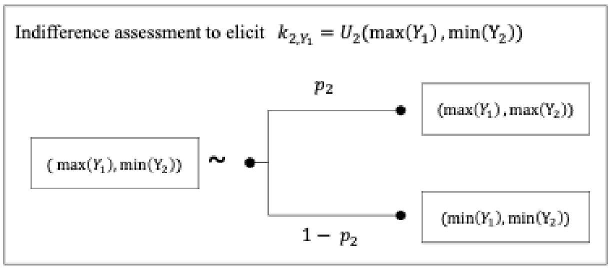


FIGURE 2.2: Indifference assessment of Corner Value from member two

- *Approximation of corner values using paired data*

In practice, if the analyst relies only on the paired data already collected, it is not possible to observe the corner values k_{1,Y_2}, k_{2,Y_1}. An approach to approximate these points on the surface is to rely on the observed minimum values of the conditional utility assessments and scale the normalized conditional utility functions using these estimates, following equations (2.22) and (2.23). However, this relies on the quality of the sample that is used, since it is uncertain what is the true minimum of the upper boundary curve, and a small sample may not include dyads where the true minima of these functions are observed.

- *Approximation of corner values using expert opinion*

Alternatively or additionally, expert opinion can be leveraged to obtain a reasonable range of values for the corner values and perform sensitivity analysis over these ranges. It is important to acknowledge the interpretation of the corner values in order to leverage expert opinion. The corner value $k_{1,Y_2} = U_1(min(Y_1), max(Y_2))$ represents the utility assessment of member one over the two-dimensional consequence $(min(Y_1), max(Y_2))$, where the consequence directly related to member two (e.g., member two health status) is fixed at its most preferred value (e.g., perfect health) and the consequence directly related to member one is fixed at its least preferred value (e.g., death).

Fixing the corner value to zero, $k_{1,Y_2} = 0$, would be equivalent to an attribute dominance utility profile, an extreme scenario where if one member of the dyad experiences their least preferred outcome (i.e., $min(Y_1)$) then the dyad collectively would also experience this outcome as the least preferred outcomes even if the other member is currently experiencing the most preferred outcome (i.e., $max(Y_2)$). In the example using health states, attribute dominance would imply that the dyad is indifferent between both members dying or if either member dies. Although possible, it would be hard and possibly unethical to work with such a system of preferences and utilities in a healthcare setting, since it would disregard any potential gains or harms that a member of the dyad would experience after the death of the other member.

The other extreme case would be for the corner value to be very close to one, i.e. $k_{1,Y_2} \approx 1$. Technically, the corner values cannot be one, because upper boundary utility functions have to be strictly increasing functions, and setting the corner value to one would make an upper boundary utility function a constant function. However, setting the corner value very close to one would represent another extreme utility profile of the dyad. In the example with health status of members of the dyad, if $k_{1,Y_2} \approx 1$, the utility assigned to the outcome where member one dies and member two experiences their most preferred outcome would be very close to the utility assigned by the dyad to the most preferred outcome overall $((max(Y_1), max(Y_2)))$. In practice, neither scenario may be useful in healthcare settings where dyadic relationships are of interest. This highlights the importance of identifying a likely range of the corner values for each member of the dyad when representing a dyadic system of utilities and quantifying via sensitivity analysis the change in dyadic utilities as we vary the corner values over the identified likely ranges.

Finally, in specific contexts it might be reasonable to fix a certain value for the corner values of the members of the dyad based on specific constraints. For example, consider the case of a dyad conformed by a patient living with a chronic disease and a caregiver. Through the progression of the disease, the health-related quality of life of the patient will deteriorate progressively and, in some cases, the deterioration will reach a point where at-home or community-based care will not be sufficient to meet their care needs and the patient will need institutionalized care. This could happen regardless of how healthy the caregiver is. Taking this into account, we could anchor the corner value of a patient living with a chronic disease to the level of quality of life that if this person goes below, they would switch to institutionalized care, instead of considering death as the least preferred outcome. This would make sense because below this value, the system of dyadic preferences will be distorted completely by the change of setting of care and will require a new complete assessment of the profile of preferences of each member of the dyad or a departure from a dyadic approach.

2.5.2 Estimation of the Polynomial Generating Function

When there is no mutual utility independence, it is necessary to estimate the parameters of the generating function (e.g., α for the quadratic generating function) in addition to the upper boundary utility curves. Here, I only consider the normalized quadratic generating function to illustrate this procedure.

The scalar parameter α of the quadratic generating function can be obtained by eliciting at least one additional point on the two-attribute utility surface (Abbas and Sun, 2019a). This can be done by interrogating the dyad members jointly. This means that we would require an additional utility assessment of the dyad, which might not be available to the researcher.

Another alternative would be to use the information on the lower boundary curves $U_{Dyad}(Y_1, min(Y_2))$ or $U_{Dyad}(min(Y_1), Y_2)$; or at any other curve at a reference value of the complementary attribute for which data are available,i.e.: identify from paired data $U_{Dyad}(Y_1, \lambda(Y_2))$, where $\lambda(.)$ is a function that returns attribute Y_2 at a reference value in the range of Y_2, for example $\lambda(Y_2) = min(Y_2)$, and where $\lambda(Y) \neq max(Y)$. Under this approach, the steps for estimating the polynomial generator would be :

1. Estimate upper boundary utility functions $U_{Dyad}(Y_1, max(Y_2)), U_{Dyad}(max(Y_1), Y_2)$, using equations (1.18) and (1.19) in the parametric case, and equations (1.20) and (1.21) if using flexible parametric models.
2. Estimate at least one reference utility function $U_{Dyad}(Y_1, \lambda(Y_2))$ or $U_{Dyad}(\lambda(Y_1), Y_2)$:
   - Case 1- Attribute Dominance: If there is attribute dominance, when either attribute is set to its minimum, the dyadic utility function is set to zero; i.e. $U_1(Y_1, min(Y_2)) = 0$, $U_2(min(Y_1), Y_2) = 0$. Instead, we need to condition at another reference value, for example very close to the minimum of the other member's utility, i.e., $U_1(Y_1 \mid \lambda(Y_2)) = U_1(Y_1 \mid min(Y_2) + \epsilon)$ or $U_2(Y_2 \mid \lambda(Y_1)) = U_2(Y_2 \mid min(Y_1) + \epsilon)$, where ϵ is a very small value.

     To obtain the dyadic utility reference curve $U_{Dyad}(Y_1, \lambda(Y_2))$ I follow the definition of conditional utility, and I illustrate this step for $U_1(Y_1 \mid \lambda(Y_2))$:

     $$U_1(Y_1 \mid \lambda(Y_2)) = \frac{U_1(Y_1, \lambda(Y_2)) - U_1(min(Y_1), \lambda(Y_2))}{U_1(max(Y_1), \lambda(Y_2)) - U_1(min(Y_1), \lambda(Y_2))} \qquad (2.24)$$

     In the AD case, the term $U_1(min(Y_1), \lambda(Y_2)) = 0$, so the expression for the dyadic utility curve at the reference value is:

$$U_1(max(Y_1), \lambda(Y_2)) * U_1(Y_1 \mid \lambda(Y_2)) = U_1(Y_1, \lambda(Y_2)) \tag{2.25}$$

Following the same logic, we obtain the expression for $U_2(Y_1, \lambda(Y_1))$ as:

$$U_2(\lambda(Y_1), max(Y_2)) * U_2(Y_2 \mid \lambda(Y_1)) = U_2(\lambda(Y_1), Y_2) \tag{2.26}$$

- Case 2 - No Attribute Dominance: In the no AD case, it is convenient to define $\lambda(Y) := min(Y)$ to simplify the expression for the dyadic utility reference curve, i.e., the lower boundary utility curves. Again, using the definition of conditional utility we can obtain the dyadic reference curves as follows:

$$\begin{aligned} U_1(Y_1 \mid \lambda(Y_2)) &= U_1(Y_1 \mid min(Y_2)) \\ &= \frac{U_1(Y_1, min(Y_2)) - U_1(min(Y_1), min(Y_2))}{U_1(max(Y_1), min(Y_2)) - U_1(min(Y_1), min(Y_2))} \end{aligned} \tag{2.27}$$

  Since $U_1(min(Y_1), min(Y_2)) = 0$, we can obtain the expression for the dyadic lower boundary utility curve $U_1(Y_1, min(Y_2))$ as:

$$k_{2,Y_1} * U_1(Y_1 \mid min(Y_2)) = U_1(Y_1, min(Y_2)) \tag{2.28}$$

  using the same logic, we obtain the dyadic lower boundary utility curve $U_2(Y_2, min(Y_1))$ as:

$$k_{1,Y_2} * U_2(Y_2 \mid min(Y_1)) = U_2(min(Y_1), Y_2) \tag{2.29}$$

  Although we could use any reference utility curve as in the AD case, using the minimum of the complementary attribute offers an advantage because the expression for $U_1(Y_1, \lambda(Y_2))$ in terms of the conditional utility simplifies when $\lambda(Y) = min(Y)$, since $U_1(min(Y_1), min(Y_2)) = 0$ in equation 2.27. In the case without AD, when $\lambda(Y) \neq min(Y)$, the term $U_1(min(Y_1), \lambda(Y_2)) \neq 0$ and has to be elicited directly from the dyad, in addition to the two corner values.

3. Finally, fit the data from the observed $U_1(Y_1, \lambda(Y_2))$ and $U_2(\lambda(Y_1), Y_2,)$ to the parameter of the polynomial generator by solving the following minimization problem:

$$\underset{\alpha \in [-1,1]}{arg\ min} \left[\sum_{i}^{n^{\lambda}} \left(U_{1,i}^{\lambda} - \hat{U}_{1,i}^{\lambda}(\hat{U}_{Y_1,max(Y_2)}, \hat{U}_{max(Y_1),Y_2}, \alpha) \right)^2 \right] \tag{2.30}$$

where the superscript $(^{\lambda})$, denotes "at the reference value", $U_{1,i}^{\lambda}$ denotes the i^{th} normalized observation of the dyadic utility at the reference value of one attribute, and $\hat{U}_{1,i}^{\lambda}(\cdot)$ denotes the i^{th} prediction of the dyadic utility at the reference value of one attribute from the Archimedean copula model that uses the estimates of the upper boundary utility curves $\hat{U}_{Y_1,max(Y_2)}$ and $\hat{U}_{max(Y_1),Y_2}$ and the quadratic generator with parameter α.

Finally, in Table 2.1[22] I summarize the different estimation targets needed depending on the preference profiles described by the assumptions made for AD and MUI.

Dyadic Preference Profile	Upper Boundary Utilities	Corner Values	Polynomial Generator
AD, MUI	yes	no	identity
AD, No MUI	yes	no	yes
No AD, MUI	yes	yes	identity
No AD, No MUI	yes	yes	yes

TABLE 2.1: Estimation Targets for each Preference Profile under the Archimedean Utility Copula Model with Polynomial Generator

2.6 Example via Simulation

DATA GENERATING PROCESS:

To illustrate the estimation steps, I rely on a simulation framework to represent a data generating process that yields two-attribute consequences of acts, and where the two attributes of consequences are possibly correlated. To further simplify this illustrative data set, I assume that the attributes $Y_1; Y_2$ refer to a hypothetical overall health-status measurements of each member of the dyad.

a. Correlated Two-attribute Consequences:

[22] Upper boundary utilities as defined in Section **2**.51, corner values as defined in equations (2.22) and (2.23), polynomial generator as defined in equation (2.8), AD: attribute dominance, MUI: mutual utility independence.

To simulate the consequences of two attributes, I use a truncated bivariate normal distribution with lower bounds $(0, 0)$ and upper bounds $(25, 25)$.

$$\begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} \sim \textit{Truncated Bivariate Normal}\left(\vec{\mu} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \Sigma = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\right)$$

where the individual means are: $\mu_1 = 12.5$; $\mu_2 = 12.5$, and correlation $\rho = 0.4$. Figure 2.3 shows the paired data on these two attributes for a simulated population of $N = 300$ dyads.

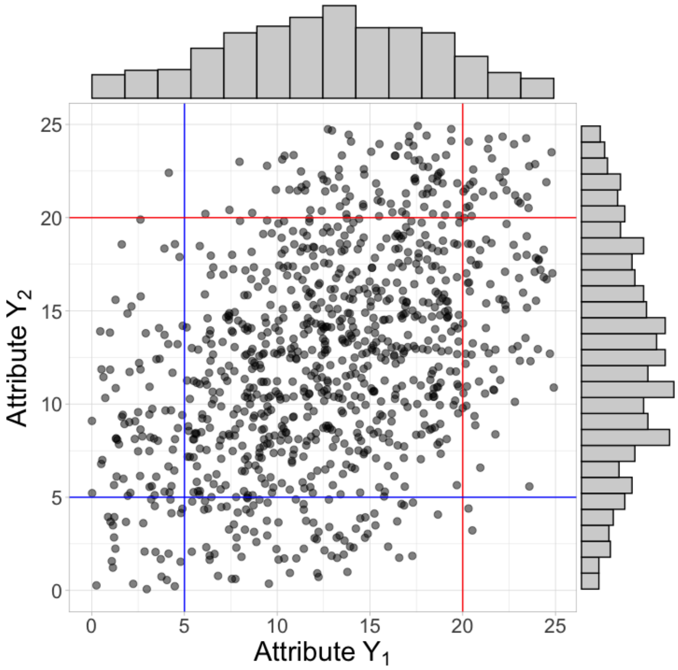


FIGURE 2.3: Two Positively Correlated Attributes

b. Regions of Best and Worst Health-status

Furthermore, since health-status measurements are simulated as continuous variables, it is necessary to discretize a subset of this domain and define regions of being at "best health-status" and "worse health status". This is because when we try to estimate the boundary utility functions, if we condition on the maximum value of one attribute we may not have enough data points to estimate the upper boundary curve. In this example I define the threshold of "best health status" to be above $\tau_{max} = 20$ and the threshold of "worst health status" to be below $\tau_{min} = 5$ (shown as blue lines in Figure 2.3). In Figure 2.3, the regions of "best health status" are shown above and to the right of the red lines, and regions of "worst health status" are shown as below and to the left of the blue lines.

c. True Upper Boundary Utilities:

For a population of dyads with homogeneous preference profiles, each type of member within the dyads follows the same individual preference profile; i.e., each member-one in the dyads follows the same preference profile at the upper boundary of the health status of member two ,$U_1(Y_1, max(Y_2))$, and each member-two in the dyads follows the same preference profile at the boundary of the health status of member one, $U_2(max(Y_1), Y_2)$. With this approach I do not consider potential heterogeneity in preferences between dyads. The analyst who wishes to employ these procedures must take the necessary steps to ensure that the sample of dyads with which they are working can be considered homogeneous in their preferences.

Both types of members follow exponential utility functions but with different risk aversion parameters $\gamma_1; \gamma_2$. This means that in this example I am assuming constant risk aversion for each member, but different risk aversion.

$$U_1(Y_1, max(Y_2)) = 1 - e^{-\gamma_1 Y_1}$$

$$U_2(max(Y_1), Y_2) = 1 - e^{-\gamma_2 Y_2}$$

where $\gamma_1 = 0.15; \gamma_2 = 0.35$.

The choice of parametric function is for illustrative purposes only and as a "ground truth" to compare the estimation procedures. In general, any continuous, bounded, strictly increasing function could be considered.

I consider the scenario of attribute dominance and also a scenario without attribute dominance. Figure 2.4 shows the two upper boundary curves that follow exponential utility models for attribute dominance (left) and no attribute dominance (right).

ESTIMATION OF NOISY BOUNDARY UTILITY CURVES

To induce measurement error in the utility measurements at the boundaries I transform the utility values at the boundaries by adding a Gaussian error term ($\epsilon \sim N(mean = 0, sd = 0.25)$) on both boundary curves. With the transformed data I show how to estimate noisy measurement of the utilities at the boundaries with a

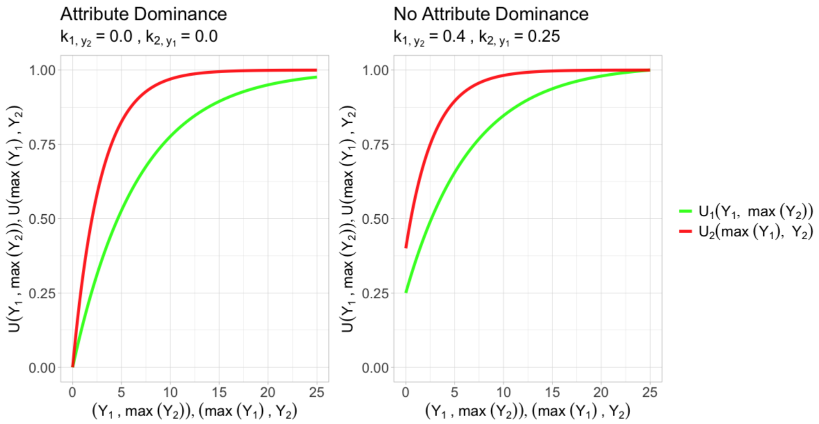


FIGURE 2.4: True Boundary Utility Curves with Attribute Dominance (left) and No Attribute Dominance (right)

parametric and non-parametric approach.

First, to estimate the upper boundary curves with the parametric approach I follow the optimization problems as proposed in equations (2.18) and (2.19), and fit the noisy data to the parameters $\gamma_1; \gamma_2$, however for the parametric case I only show this procedure for the Attribute Dominance scenario. I obtain the solution to the least squares problems using the "nls" function in the R statistical software and obtain estimates of the parameters: $\hat{\gamma}_1 = 0.149; \quad sd_1 = 0.008$; $\hat{\gamma}_2 = 0.31, \quad sd_2 = 0.02$. Figure 2.5 shows the predicted upper utility curves in the attributed dominance case that result from fitting the noisy data at the boundaries to the parameters of the exponential functions under attribute dominance.

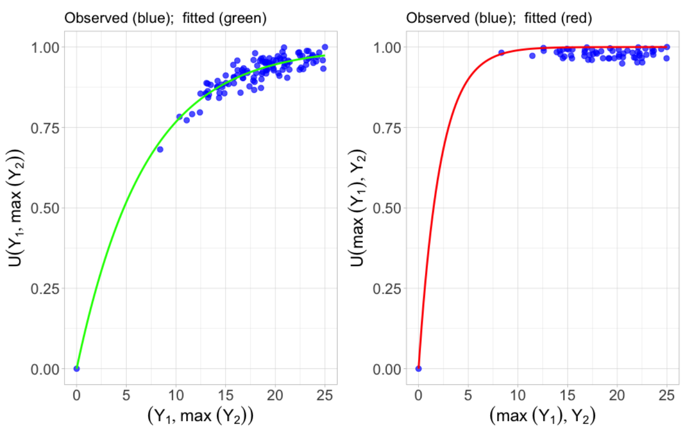


FIGURE 2.5: Fitted Upper Boundary Utilities to Parametric Model, Attribute Dominance

Second, in the no attribute dominance case, we need to estimate or fix the corner values of the utility surface. In this illustration I simplify this step by assuming that we have enough domain expertise or we elicited directly the corner values from the members of the dyad to set these values to $k_{Y_1} = 0.4$ and $k_{Y_2} = 0.25$. Then, we can approximate the solution to equations (2.20) and (2.21). I fit the noisy data at the boundaries to monotonically constrained smoothing splines and obtain approximations to the upper boundary utility functions as shown in Figure 2.6. For both upper boundary curves the specification of the spline included 8 knots and the smoothing parameter was set to $\lambda = 3$. No cross-validation to determine λ was done for this example.

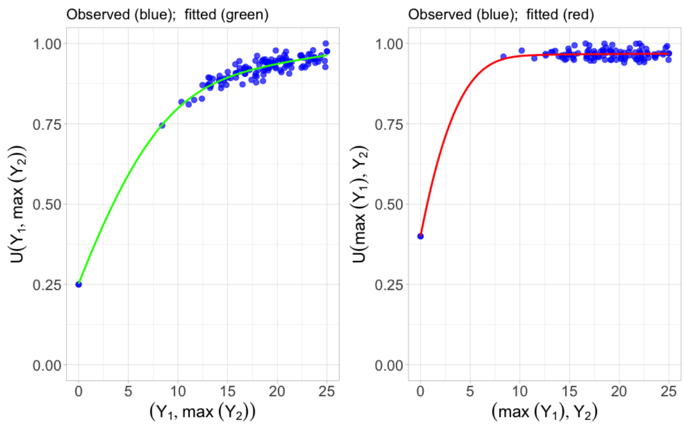


FIGURE 2.6: Fitted Upper Boundary Utilities to Smoothing Spline Model, No Attribute Dominance

ESTIMATION OF THE QUADRATIC GENERATOR

Finally, the last step is to estimate the generator of the copula. There is little guidance on how to approach this problem in practice. We can interrogate the dyad and assess a couple of points on the surface of the dyadic utility function and substitute them to determine α, however if we only have access to collected paired utilities of each member this approach is not feasible. A heuristic approach in the case of the Archimedean copula would rely on the empirical rank-correlation (Kendall's τ) of the marginal utility vectors of each member of the dyad and use it as an approximation for the parameter of the quadratic generator. Figure 2.7 shows the obtained utility surface in the attribute dominance case, using this heuristic.

Similarly, Figure 2.8 shows the utility surface in the case without attribute dominance and setting the parameter of the generator function to the observed correlation. The corner values k_{1,Y_2} and k_{2,Y_1} are highlighted in red.

Alternatively, we can leverage the observed utilities at the lower boundaries, i.e., in the regions I defined as "worst health-status" shown in Figure 2.3. Solving the

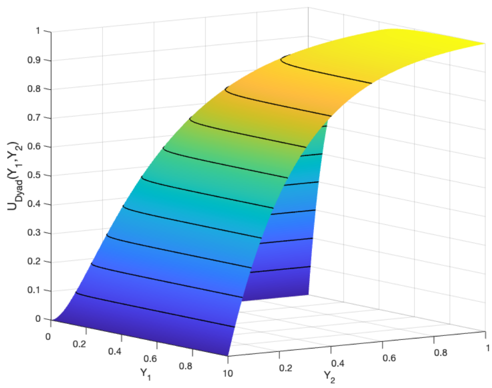


FIGURE 2.7: Dyadic Utility Surface, Attribute Dominance

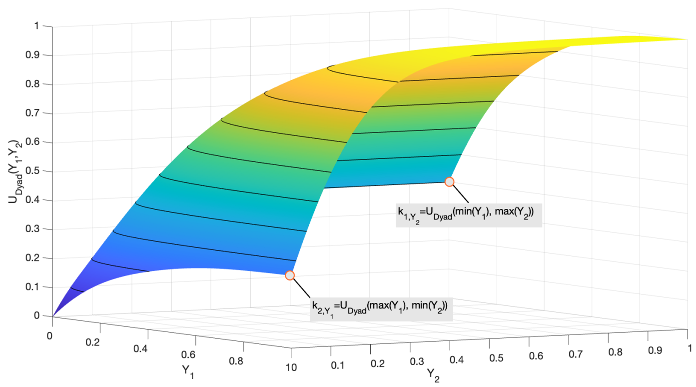


FIGURE 2.8: Dyadic Utility Surface, No Attribute Dominance

minimization problem in equation 2.30, the optimal value of $alpha$ that minimizes the quadratic loss to the observed lower boundary curve is $alpha^* = 0.71$ and yields a quadratic loss of $SSE_{alpha^*} = 0.079$. In contrast, using the rank correlation $\alpha = \tau = 0.5$ yields a quadratic loss of $SSE = 0.237$.

In Figure 2.9, I contrast visually both surfaces, to illustrate the improved fit after calibrating the dyadic utility surface to the observed lower boundary dyadic utilities following equation 2.30. The red surface represents the dyadic utilities estimated by setting $\alpha = \tau$, and the blue surface represents the dyadic utilities by setting α to the optimal value, $\alpha = \alpha^*$. Black dots represent the simulated theoretical values of the lower boundary utility curve. The comparison shows that the improvement in the fit of the surface occurs mainly at the lower values of the dyadic utilities. Further validation of this approach is left as an important avenue to explore in future work.

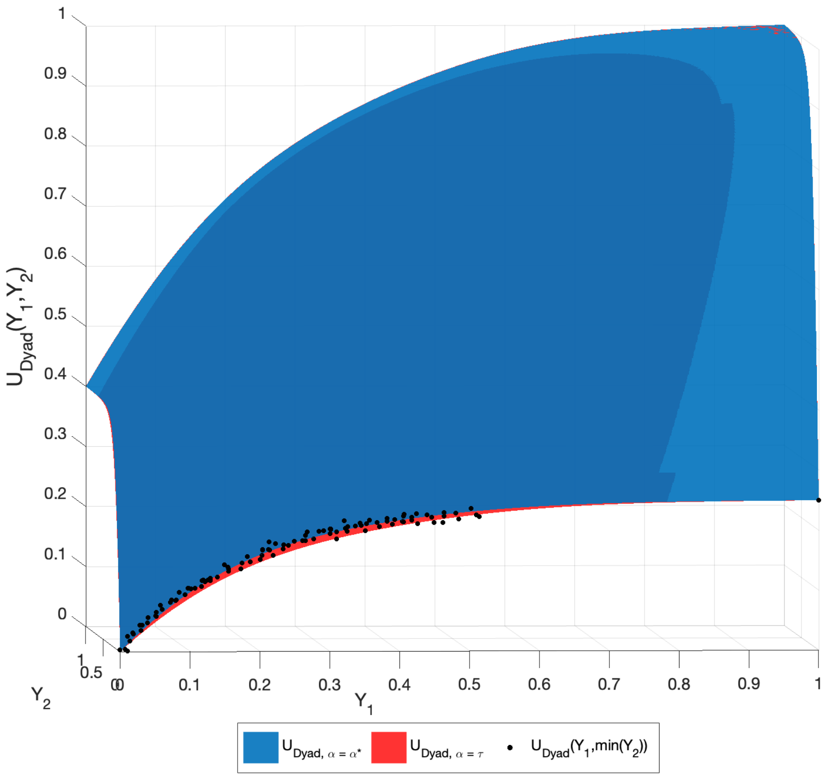


FIGURE 2.9: Fitting Lower Boundary Curve to Quadratic Generator, No Attribute Dominance

2.7 Conclusion

In this chapter, I first define decision problems in which I consider a structured entity conformed by two beneficiaries that I refer to as a dyad or a population of dyads. In contrast to the predominant theories of choice, in which members of the dyad must choose over acts (i.e., decision alternatives) individualistically without considering consequences that may affect the other member of the dyad, I propose a collective decision rule under which the dyad can decide collectively over acts that may affect them both. Importantly, I develop conditions under which the proposed decision rule preserves a weak order over the set of possible acts (complete and transitivity preferences) and conditions under which both members of the dyad can agree on a unique preferred choice over acts (symmetric awareness, additive ordinal preferences, and mutual agreement). The resulting dyadic ordinal preference function under these conditions is presented in a well-known functional form (additive ordinal preferences) and is leveraged as the foundation for the construction of a dyadic utility function under which the dyad can decide over acts with risky consequences, i.e., acts whose consequences can occur as described by a known probability measure.

Secondly, I use the most general form of utility functions over risky consequences that correspond to additive ordinal preferences and are strictly increasing with each attribute when the complementary attribute is fixed at the maximum value (Archimedean utility copula function) to represent the dyadic utilities, and illustrate the flexibility that this form offers in terms of representing a wide range of utility profiles for the dyad. These profiles may include cases where there is utility dependence and/or attribute dominance, as well as their their antithetical cases; thus providing a useful representation of utility profiles of dyads in diverse settings in healthcare and medical decisions.

Finally, via simulation of paired consequences, I illustrate different approaches for estimating the dyadic Archimedean utility copula assuming different utility profiles of the dyad and define the additional assumptions that are required in order to do the estimation using paired data, direct utility elicitation, or expert judgement.

The proposed dyadic Archimedean copula is an important contribution, since it extends the spillover framework by explicitly acknowledging the potential dependence between the utility valuations of the members of the dyad (i.e., relaxing mutual utility independence). Additionally, by relaxing attribute dominance, the dyadic Archimedean utility function offers a more principled approach to capturing the utility of the dyad when one member experiences an extreme outcome; e.g.: when one member in the dyad dies but we wish to asses the utility that the alive member experiences forward. Finally, for specific dyadic utility profiles(e.g. attribute dominance), the Archimedean copula formulation offers the option to estimate its parameters only from previously collected paired data on the individual utilities of the members of the dyad without relying on additional utility elicitation efforts that involve the dyads. In these instances, our method can greatly reduce the cognitive burden imposed on a dyad to elicit their joint utilities and can potentially reduce the cost of such studies. Additionally, in the instances where we need to relax attribute dominance, reduced cognitive burden and costs are still attainable at the expense of having to make additional, and in some cases, reasonable assumptions about the utilities of the members of the dyad at the corner values.

Finally, the dyadic Archimedean copula has important limitations. First, this approach relies on existing evidence on the ordinal preferences and utilities over health outcomes of dyads, which is scarce. In most real-world situations there is only indirect evidence (e.g., non-preference based measured of health-related quality of life) of the dyadic preferences and utilities, as well as small samples on dyads. These limit the researcher's capacity to accurately and generally characterize the system of utilities over paired outcomes of the dyads and their capacity to validate the estimation of dyadic utilities against a gold standard. Second, to verify the assumptions imposed to guarantee a dyadic Archimedean utility copula function, the researcher most have direct access to the dyad(s). When access to the dyad(s) is not available, expert judgement from clinicians is needed in conjunction with the available data on the individual utilities. When access to dyad(s) and experts is not available, the paired data may not be sufficient to characterize the dyadic utility function. Finally, a thorough sensitivity analysis must accompany the estimation of dyadic utilities to quantify uncertainty over the copula parameters that are rarely reported in the literature or are cognitively demanding to assess directly from the dyads (e.g. corner values and quadratic generator parameter).

Chapter 3

Individual and Dyadic Health-Related Quality of Life of People Living with Dementia and their Caregivers

Abstract

Background Many interventions jointly target dyads of people living with Alzheimer's disease and related dementias (ADRD) and their caregivers. Without a dyadic measure of health-related quality of life (HRQOL), cost-utility analyses of these interventions require using the HRQOL of people with ADRD and caregivers, separately. The objective of this study is to develop a dyadic measure of HRQOL that incorporates the interdependence between HRQOL of people living with ADRD and their caregivers. First, we estimated dyadic HRQOL time trade-off-weights (TTO-weights), a dyadic preference-based measure of HRQOL. Second, we estimated the association between ADRD clinical features and TTO-weights. **Methods** We used the Aging, Demographics, and Memory Study (ADAMS) to identify people living with ADRD (n=308) and their caregivers (n=160 dyads) and predict their HRQOL TTO-weights. We estimated dyadic TTO-weights using an Archimedean bivariate utility copula with a quadratic generating function. Second, we used adjusted linear regression to examine the association between predicted TTO-weights and ADRD clinical features. **Results** Average (standard deviation) TTO-weights of people living with ADRD and caregivers were 0.67 (0.14) and 0.83 (0.09), respectively. Average dyadic TTO-weight was 0.75(0.05). An additional functional limitation resulted in more than twice the decline in the TTO-weight of people living with ADRD compared to an additional behavioral symptom (-0.008vs. -0.003). Behavioral symptoms were significantly associated with a decline in caregivers' and dyadic TTO-weights. **Conclusions** The HRQOL of people living with ADRD and their caregivers

are correlated. The dyadic TTO-weights for people living with ADRD and their caregivers can be used in cost-utility analyses of interventions that target dyads.
Keywords: Health-related Quality of Life; Alzheimer's Disease and Related Dementias (ADRD); Multi-attribute Utility; Copula Modeling; Dyadic Analysis; Medical Decision Making

3.1 Introduction

Alzheimer's disease and related dementias (ADRD) affect 50 million people worldwide (WHO, 2017). People living with ADRD experience declines in cognitive and functional abilities and many exhibit behavioral symptoms (e.g., hallucinations and wandering). Most people living with ADRD live in the community, and they receive a large amount of care from family and friends caregivers (Friedman et al., 2015).

Randomized trials of non-pharmacologic psychosocial dyadic interventions have demonstrated clinically and statistically significant improvement in outcomes for people living with ADRD and their caregivers (Oliveira et al., 2015; Gitlin et al., 2010a; NASEM, 2021a; Samus et al., 2014). The benefits of these interventions include reducing behavioral symptoms, reducing the need for assistance with functional activities, reducing the risk of moving to a nursing home, and improving health-related quality of life (HRQOL). A growing literature has also found that non-pharmacologic dementia care interventions are cost-effective (Gitlin et al., 2010b; Graff et al., 2008; Nickel, Barth, and Kolominsky-Rabas, 2018; Shaw et al., 2021; Vandepitte et al., 2020).

Quality-adjusted life years (QALYs) are outcome measures used in cost-utility analysis (Wolowacz et al., 2016). QAYLs combine a preference-based measure of HRQOL (e.g., morbidity) and mortality (e.g., remaining lifetime) on a single scale (Neumann et al., 2016b) and are computed by multiplying each year a person is alive with the HRQOL for those years. In this study, we focus on time trade-off (TTO)-weights as a preference-based measure of HRQOL (Hunink et al., 2014). To obtain TTO-weights, respondents are given two choices: 1) live their remaining life at their current level of HRQOL, or 2) live a fraction (x) of their remaining life in perfect health (described as a state without health problems). Respondents are asked to indicate the duration of (x) such that they are indifferent between the two options. The value they indicate for (x) is the TTO-weight for their current level of HRQOL (Figure B.1 and B.2 in Appendix B). TTO-weights are typically scaled to range between zero and one, where zero is interpreted as the worst HRQOL(e.g., dead), and one is interpreted as the best possible HRQOL (Torrance, 1970; Lugnér and Krabbe, 2020; Lipman, Brouwer, and Attema, 2020).

Cost-utility analyses of non-pharmacologic dementia care interventions are often conducted independently from the perspective of a person living with ADRD or their caregiver. That is, a decision-maker separately evaluates cost-effectiveness of interventions based on the person living with ADRD's QALYs or caregiver's QALYs.

This approach ignores potential trade-offs between a person living with ADRD's QALYs and their caregiver's QALYs, and does not consider the association (i.e., dependence) between the HRQOL of a person living with ADRD and the HRQOL of their caregiver (Canam and Acorn, 1999). Ignoring this association means that interventions that improve HRQOL may underestimate (positive correlation between a person with ADRD's HRQOL and a caregiver's HRQOL) or overestimate (negative correlation between a person with ADRD's HRQOL and a caregiver's HRQOL) cost-effectiveness. Looking collectively at the person living with ADRD's and the caregiver's HRQOL using a single measure that accounts for their association can overcome these limitations and support decision-makers in evaluating interventions that target dyads. To our knowledge, no such measure exists.

One approach to construct a dyadic measure of HRQOL is to interview each member of a dyad about their HRQOL conditional on the other member of the dyad's HRQOL (Basu et al., 2010). This approach provides a complete characterization of the HRQOL of the dyad members while accounting for their association; however, it can be time-consuming, cognitively demanding, requires large samples, and is costly. To our knowledge, no study has applied this approach to people living with ADRD and their caregivers. A second approach is to obtain paired HRQOL estimates for members of the dyad and combine them into a single measure. Under the assumption that the measures of the HRQOL are independent, additively or multiplicatively combining them into a single measure of HRQOL is a practical approach (Keeney, Raiffa, and Meyer, 1993). However, the assumption of independence is difficult to verify and may not be appropriate in some contexts. Alternatively, separate estimates can be combined using mathematical methods that account for the association between members of the dyad.

Multi-attribute utility copula (MAUC) is a flexible framework based on copula theory, a statistical methodology to model dependencies between random variables (Nelsen, 2006). In decision-making, MAUCs are used to combine and model dependencies between preference-based measures (e.g., TTO-weights) (Abbas, 2009). In particular, Archimedean MAUCs model the dependencies between preference-based measures via a one-parameter function (Abbas and Sun, 2019b). Additionally, Archimedean MAUCs can model non-dominated preferences, which means that a dyadic HRQOL measure constructed via Archimedean MAUC is not zero if one member of the dyad dies (Abbas, 2018b; Abbas and Sun, 2015b). This is necessary to accurately assess the HRQOL over the lifetime of the members of the dyad since, in most cases, the end of life of each member of the dyad will occur at different times.

In this study, we use Archimedean MAUC to combine the preference-based measures of HRQOL of people living with ADRD and their caregivers. Specifically, we construct dyadic TTO-weights that represent the fraction (x_D) of remaining life years such that the dyad is indifferent between two choices: live their remaining life years at their current HRQOL, or live that fraction (x_D) of remaining life years if they could both live it in perfect health. To obtain the dyadic TTO-weights, we first predict TTO-weights for people living with ADRD and their caregivers separately using previously published regression models. Then, we combine the separately obtained TTO-weights into dyadic TTO-weights using Archimedean MAUC. Finally, via regression analysis, we assess the hypothesis that the predicted individual and dyadic TTO- weights are associated with ADRD clinical features of cognition, functional activity limitations, and behavioral symptoms.

3.2 Methods

3.2.1 Sample and Data

We used Wave A (2000) data from the Aging, Demographics, and Memory Study (ADAMS), which is a United States population-based survey on the factors, costs, and outcomes associated with dementia (Langa et al., 2005). ADAMS respondents were randomly sampled from Health and Retirement Study (HRS) participants ($\geq$ 70 years of age), which is a longitudinal nationally representative survey of older Americans (Juster and Suzman, 1995). ADAMS respondents participated in an in-home clinical battery, which included cognitive, physical function, behavior, and psychological assessments. An informant also participated in the ADAMS survey and reported whether they provided any caregiving to the respondent. Following the in-home assessment, a neuropsychologist, neurologists, gero-psychiatrists, and internists determined whether a respondent had dementia, cognitive impairment not dementia, or normal cognitive function (Langa et al., 2005). We identified ADAMS Wave A respondents with dementia. Of these respondents, we determined whether the respondent's informant identified as their caregiver based on the informant's response to the question: "In the past month, have you provided care to your friend or relative (. . .)".

3.2.2 Clinical Features and Characteristics of People living with ADRD and Caregivers

The cognitive function of ADAMS respondents was assessed using the Mini-mental State Exam (MMSE; scored 0-30) (Folstein, Folstein, and McHugh, 1975). We determined whether respondents reported any limitations or inability to perform 10 different functional activities of daily living (scored $0 - 10$) (Table B.1 in Appendix B) (Mayo, 2016). The number of behavioral symptoms (0-12) exhibited by respondents was assessed using the Neuropsychiatric Inventory Questionnaire (NPI), which consists of 12 domains: 1) Delusions, 2) Hallucinations, 3) Agitation/Aggression, 4) Depression/Dysphoria, 5) Anxiety, 6) Elation/Euphoria, 7) Apathy/Indifference, 8) Disinhibition, 9) Irritability/Lability, 10) Aberrant/Moto, 11) Nighttime Behaviors, and 12) Appetite/Eating. Finally, we obtained each respondent's and caregiver's age, sex, race, educational attainment, marital status, income, and the caregiver's relationship to the person with dementia.

3.2.3 From Self-reported Health Status to Predicted TTO-Weights

Nyman et al. (2007) published multivariate linear models that relate self-reported health-status categories ("poor", "fair", "good", "very good", or "excellent") and TTO-weights using nationally representative data from the Medical Expenditure Panel Survey (MEPS) (Nyman et al., 2007). To estimate these models, they first identified MEPS respondents' self-reported health-status categories and EQ-5D-3L health state responses. Second, they assigned the corresponding TTO-weights to the EQ-5D-3L health states following the approach in Shaw et al. (Shaw, Johnson, and Coons, 2005). Finally, Nyman et al. (2007) fitted multivariate linear regression models to predict TTO-weights (derived TTO- from the EQ-5D-3L) as a function of self-reported health status categories, sex, race, age, income, educational attainment, and marital status.

We used Nyman et al.'s. published regression coefficients to predict two sets of TTO-weights for ADAMS respondents: one set of predicted TTO-weights for people living with ADRD (TTO_{ADRD}), and a second set of predicted TTO-weights for their corresponding caregivers (TTO_{cg}). ADAMS provides the necessary inputs to predict these two sets of TTO-weights since both types of respondents provided responses on the same self-reported health status and sociodemographic characteristics as used in Nyman et al(2007). This step is illustrated as Step 1 in Figure 3.1 During the ADAMS survey, caregivers were not asked to report their income; we assumed the same household income for the respondent and the caregiver. Finally, we used mean imputation for 12 respondents who had missing data on household income.

3.2.4 From Predicted Individual TTO-weights to Dyadic TTO-weights

With the two sets of predicted TTO-weights (TTO_{ADRD},TTO_{cg}) we constructed a set of dyadic TTO-weights (TTO_{Dyad}) that represent the preference-based measures of the collective health-related quality of life of the members of the dyad (see Step 2 in Figure 3.1). To account for the dependency between TTO_{ADRD} and TTO_{cg} when computing the combined measure TTO_{Dyad}, we leveraged a copula approach, which is a well-established statistical method for modeling dependencies among random variables (Nelsen, 2006). We used a specific class of copulas, i.e., a bivariate Archimedean copula that allows various trade-offs among its arguments (attributes) (Abbas and Sun, 2019b). In our two-attribute case (i.e., TTO_{ADRD} and TTO_{cg}), we compute TTO_{Dyad} using the following Archimedean copula function:

$$C\Big(TTO_{ADRD,max(cg)}, TTO_{max(ADRD),cg}\Big) = g_{\alpha}^{-1}\Big[g_{\alpha}(TTO_{ADRD,max(cg)}) * g_{\alpha}(TTO_{max(ADRD),cg})\Big]$$

where g_{α} and $g_{\alpha}^{-1}(.)$ are a quadratic generating function and its inverse, respectively. Intuitively, the Archimedean utility copula transforms its inputs, which are the two boundary TTO-weights (i.e., $TTO_{ADRD,max(cg)}$ and $TTO_{max(ADRD),cg}$, and combines them into a single dyadic TTO-weight on a $0,1$ scale. The boundary TTO-weights are the predicted TTO-weights of one member of the dyad when the other member of the dyad's predicted TTO-weights are fixed at their theoretical highest value of one. The role of the generating function is to transform the boundary TTO-weights from the $0,1$ scale to an unbounded scale, which permits calculations in a non-restrictive manner. The inverse of the generating function ensures that the output from the calculation is confined to the original $0,1$ scale. The calculation also depends on the parameter of the quadratic generating function (α) that controls the strength of the dependence between the individual TTO-weights. We refer the interested readers to Appendix B for the mathematical formulation of the two-attribute Archimedean copula and the test of consistency of the quadratic generating function to our data.

To obtain the boundary TTO-weights in the paired sample we defined TTO-weights > 0.80, to be "highest", which corresponds with "excellent" self-reported health status (Nyman et al., 2007). Therefore, in the paired sample, we identified the observed boundary TTO-weights for people living with ADRD as the predicted TTO-weights for people living with ADRD whose caregivers had TTO-weights > 0.80. Similarly, we identified the observed boundary TTO-weights of caregivers as the predicted TTO-weights whose care recipients with ADRD had TTO-weights > 0.80. Using the observed boundary TTO-weights we fitted monotonically constrained smoothing splines (MCSS) (Ramsay, 1998b). With the MCSS we predicted two sets of boundary TTO-weights from the observed minima (0.446 for people living with ADRD and 0.51 for caregivers) to the theoretical maxima of one. To minimize the error of the out-of-sample predictions of the MCSS, we determined the optimal smoothing parameter (δ) of the MCSS via 5-fold cross-validation, resampling the boundary TTO-weights to find the specification of (δ) that minimized the prediction error. Additionally, we evaluated the sensitivity of our results to the choice of different thresholds $(0.75 - 0.84)$.

Finally, we used the sample estimate of Kendall's tau rank-correlation between the paired predicted TTO-weights of people living with ADRD and their caregivers to parameterize the quadratic generating function of the Archimedean utility copula, and together with the predicted boundary TTO-weights we obtained the dyadic TTO-weights. We graphed iso-value curves to examine the combinations of individual TTO-weights that comprise the same dyadic TTO-weights and to represent the potential trade-offs decision-makers may incur in when choosing between interventions that target people living with ADRD and their caregivers.

3.2.5 Association between Predicted TTO-weights and ADRD Clinical Features

We used multivariate linear regression to examine the association between the individual and dyadic TTO-weights with the ADRD clinical features (cognition, functional activity, and behaviors) controlling for sociodemographic characteristics of the dyad. We used multiple imputation (25 imputed data sets) to account for missing data on the independent variables of the regression models (Carpenter and Kenward, 2012). The first regression examined the association between people living with ADRD's TTO-weights (outcome measure) and their clinical features, controlling for the place of residence, age, gender, race, marital status, and education. The second regression examined the association between the caregiver's TTO-weights (outcome measure) and the person living with ADRD's clinical features. This regression controlled for the caregiver's age, gender, race, marital status, education, and relationship to the person living with ADRD. The third regression examined the association between the dyadic TTO-weights (outcome measure) and the person living with ADRD's clinical features while controlling for the person living with ADRD's and caregiver's demographics.

3.3 Results

3.3.1 Sample Characteristics

We identified 308 people living with ADRD and a subsample of 160 dyads (paired observations of people living with ADRD and a caregiver) that met our study inclusion criteria (Figure 3.2). On average (SD), people living with ADRD in the full sample ($n = 308$) were 85.3 years old (7.0); 69.2% were female, 65.3% were widowed, and 24% were living in a nursing home at the time of their ADAMS assessment. These people had an average MMSE score of 14.3 (6.4), 6.6 (2.1) functional activity limitations, and 2.8 (2.4) behavioral symptoms. The subsample of people living with ADRD who had a caregiver ($n = 160$) was similar to people in the full sample. Caregivers in the dyadic sample ($n = 160$) were on average 60.4 years old (13.6) with 70% and 72% of them were female and married, respectively (Table 3.1).

3.3.2 Self-reported Health

Of the 308 people living with ADRD, 3.6% ($n = 11$) reported being in excellent health, 15.6% ($n = 48$) in very good health, 21.8% ($n = 67$) in good health, 29.5% ($n = 91$) in fair health, and 29.5% ($n = 91$) in poor health. In the dyadic sample ($n = 160$), a higher proportion of people living with ADRD reported being in health states on the lower end of the scale (excellent 3.8% ($n = 6$), very good 15.0% ($n = 24$), good 25.6% ($n = 41$), fair, 27.5% ($n = 44$), and poor, 28.1% ($n = 45$)); compared to caregivers (excellent 17.5% ($n = 28$), very good 28.8% ($n = 46$), good 30.6% ($n = 49$); fair, 20.6% ($n = 33$); and poor, 2.5% ($n = 4$) (Table 3.2).

3.3.3 People living with ADRDs', Caregivers', and Dyadic TTO-weights

In the full sample ($n = 308$), the average TTO-weights of people living with ADRD was 0.67 (SD: 0.14; range: $0.43 - 0.89$). In the dyadic sample ($n = 160$), the average TTO-weights of people living with ADRD and caregivers were 0.67 (SD: 0.14; range $0.44 - .89$) and 0.83 (SD 0.09; range $0.51 - 0.96$), respectively (Table 3.2). The average dyadic TTO-weight ($n = 160$) was 0.75 (SD=0.05; range $0.62 - 0.87$) (Figure 3.3; and Table B.3 in Appendix B). Results were not sensitive to the choice of thresholds to determine the highest TTO-weights (Figure B.4 Appendix B).

Individual TTO-weights that yield the same combined TTO-weight are shown in the iso-value curves in Figure 3.4. When the TTO-weights are ≤ 0.60, the iso-value curves are convex towards the origin, representing non-proportional tradeoffs between the TTO-weight of people living with ADRD and caregivers. When the TTO-weights are > 0.60, the iso-value curves exhibit a quasi-linear relationship representing tradeoffs that are approximately constant. Additionally, Table B.4 in Appendix B provides numeric values of pairs of individual TTO-weights and the corresponding dyadic TTO-weights

3.3.4 Association between Dementia Clinical Features, Individual TTO-weights, and Dyadic TTO-weights

In the full sample of people living with ADRD, functional activity limitations and behavioral symptoms were associated with a -0.008 (95% CI: -0.015, -0.0001) and -0.003 (95% CI: -0.010, 005) decrease in TTO-weight, respectively. Cognition was not significantly associated with the person living with ADRD's TTO-weights. In the dyadic subsample, functional activity limitations (-0.006 95% CI: -0.019, 0.006) and behavioral symptoms (-0.006 95% CI: -0.015, 0.004) were negatively but not statistically associated with TTO-weights of the person living with ADRD. Among caregivers, the number of behavioral symptoms exhibited by people living with ADRD was statistically associated with a -0.006 (95% CI: -0.012, -0.001) decrease in the caregiver's TTO-weight. The person living with ADRD's functional activity limitations and cognition were not significantly associated with the caregiver's TTO-weight. Finally, the number of behavioral symptoms was statistically associated with a -0.004 (95% CI: -0.007, -0.001) decrease in the dyadic TTO-weights (Table 3.3).

3.4 Discussion

Our study provides the first dyadic TTO-weights of people living with ADRD and their caregivers. The dyadic TTO-weights address the need for a preference-based measure of dyadic HRQOL that can be used in cost-utility analysis of interventions targeting people living with ADRD and their caregivers jointly. Investigators that only collect paired individual TTO-weights for members of an ADRD dyad can use Figure 3.4 or Table B.4 to identify the dyadic TTO-weights. In addition, we examined the association between dementia-related clinical features and TTO-weights, which can be used to infer the potential HRQOL benefits associated with interventions that ameliorate these symptoms.

Our dyadic TTO-weights are useful because they explicitly quantify the impact of multi-objective interventions on a single metric and can be used by decision-makers to assess the potential benefits to the dyad. Without a combined TTO-weight, decision-makers must assess the impact of dyadic interventions separately for each member of the dyad and ignore the association in HRQOL outcomes between the dyad members. For example, suppose a dyad has a combined TTO-weight of 0.49, where the person with ADRD has a TTO-weight of 0.25 and the caregiver a TTO-weight of 0.60. If an intervention increases the person living with ADRD's TTO-weight by 0.05 (from 0.25 to 0.3), all else constant, the combined TTO-weight will increase to approximately 0.54. Instead, if an intervention increased the caregivers' TTO-weight by 0.05 (from 0.60 to 0.65), all else constant, the combined TTO-weight would increase to approximately 0.51. For this dyad, where the caregiver had a higher HRQOL at baseline, an intervention that further increases the TTO-weight of the caregiver will yield a considerably smaller increase in the combined TTO-weight compared to an intervention that increases the TTO-weight of the person with ADRD by the same amount (Figure 3.4, and Table B.4 in Appendix B).

To date, most randomized trials of ADRD interventions have not been designed to evaluate cost-effectiveness. Specifically, these trials often do not directly elicit preference-based HRQOL. However, for trials that capture functional activity limitations or behaviors, the coefficients from our regression and dyadic analyses can be used to infer changes in TTO-weights for the people living with ADRD and their caregivers separately, as well as in dyads.

With the Archimedean utility copula, we were able to account for the dependence between the TTO-weights within dyads. In comparison, additively or multiplicatively combining the individual TTO-weights assumes mutual independence (see multilinear models proposed in (Keeney, Raiffa, and Meyer, 1993) . In the context of ADRD, this assumption is problematic since we found that the TTO-weights are positively correlated (the rank-correlation coefficient was 0.12). Ignoring this dependence in the computation of a dyadic TTO-weight may underestimate the value of an intervention.

The Archimedean utility copula also guarantees that whenever a dyad member dies (i.e., her individual TTO-weight is zero), the dyadic TTO-weight will be nonzero, (Abbas and Sun, 2019b), allowing to quantify QALYs over lifetime time horizons. In contrast, Libby and Novick, (1982) proposed a two-attribute model from the cumulative distribution function of a bivariate Beta random variable (Libby and Novick, 1982). However, multi-attribute utility models that rely on cumulative distribution functions can only be used under the assumption of dominance (Abbas, 2018b; Abbas and Sun, 2015b), which is undesirable in the dyadic case. Truncating the dyadic health-related quality of life weight and setting it to zero when one member of the dyad dies may bias downwards the estimation of the gained QALYs over a lifetime. For example, when assessing interventions that teach caregivers coping skills, if the person with dementia dies, the caregivers' coping skills will extend after this event, and it would be desirable to capture the associated benefits. In contrast, a model that assumes dominance would assume no more benefit for the dyad after the person with dementia dies.

There are several design choices to consider when using the combined TTO-weight. First, a decision must be made about how to account for mortality within the dyad. Even when one of the dyad-members is at the lowest HRQOL(i.e., dead), the dyadic TTO-weights correspond to a non-zero value that accounts for the HRQOL of the dyad member still alive. Practically, this means it is feasible to evaluate cost-effectiveness so long as one person within the dyad remains alive. Conceptually, there is limited theoretical guidance on whether to anchor the analysis on the person with ADRD's survival, the caregiver's survival, or to use the maximum survival of the dyad. Second, if a combined TTO-weight is used, then it is important to include the costs for both measures of the dyad when calculating the incremental cost-effectiveness ratio.

Our study has several limitations. First, our sample of dyads ($n = 160$) did not capture the full range of the theoretical distribution $(0, 1)$ of TTO-weights. Therefore, we used thresholds to define the maximum TTO-weights of the members of the dyad and fitted flexible parametric models (smoothing splines) to extrapolate the boundary TTO-weights from the observed minima to the theoretical maxima of one. To minimize the error of the out-of-sample predictions, we determined the optimal smoothing parameter of the spline models via cross-validation, which minimized the prediction error. A related limitation is that to obtain the dyadic TTO-weights, we used a deterministic utility copula and did not account for uncertainty in the predicted dyadic TTO-weights.

Second, we used the regression models of (Abbas, 2018b) that rely on the mapping from EQ-5D-3L responses to TTO-weights. This may be a limitation. The EQ-5D-3L is a generic rather than a disease-specific measure of HRQOL; however, others have found that the EQ-5D-3L is a valid preference-based measure for people living with ADRD (Easton et al., 2018; Li et al., 2018). For example, Michalowski et al.(2020) compared EQ-5D-3L with the Quality of Life in Alzheimer's Diseases (QoL-AD) and concluded that EQ-5D-3L performed comparably with the QoL-AD, and was appropriate in economic evaluations in dementia (Michalowsky et al., 2020).

Third, another potential limitation with TTO-weights is that they may not capture the severity of health states considered worse than dead (M. Gandhi, 2019). However, in our study, none of the predicted TTO-weights correspond to states worse than dead (i.e., TTO-weights < 0).

Fourth, several studies have evaluated health utilities for people living with ADRD by disease stage (e.g., mild, moderate, and severe)(Landeiro et al., 2020; Neumann et al., 1999). Our analysis does not incorporate a measure of disease stage. Instead, we evaluated the association between ADRD clinical features and TTO-weights. Importantly, we find that ADRD behavioral symptoms are significantly associated with caregiver HRQOL; yet, behavioral symptoms are generally not used in staging ADRD (as in the case of the Clinical Dementia Rating) (Jutkowitz et al., 2017a; Jutkowitz et al., 2017b). Investigators interested in understanding how TTO-weights change as ADRD clinical measures change can consult the reported coefficients in Table 3.3. Investigators can also predict TTO-weights for people with specific levels of cognition, the number of functional limitations, and behavioral symptoms.

Finally, we cannot rule out the potential for bias due to regression to the mean (Fayers and Hays, 2014)in the equations in (Nyman et al., 2007). To correct for this possible bias (e.g., under-predict high scores and over-predict low scores) following a linear equating approach (Lamu, 2020)requires the source data that Nyman et al. 2007 used in their analyses. The Nyman study only reports the regression coefficients, which allow obtaining the predicted TTO-weights, but the TTO-weights derived from the EQ-5D-3L values are not available from the study, prohibiting a linear equating correction.

3.5 Conclusion

The health-related quality of life of people living with ADRD and their caregivers are interrelated. Our dyadic TTO-weights for people living with ADRD and their caregivers account for the association in health-related quality of life between members of the dyad. The dyadic TTO-weights can be used as an outcome measure to evaluate interventions that target people living with ADRD and their caregivers.

3.6 Tables

TABLE 3.1: Sample Characteristics

	Full Sample (n=308 obs.)	Paired Sample (n=160 paired obs.)	
	People living with ADRD	People living with ADRD	Caregiver
Female, n(%)	213 (69.2%)	110 (68.8%)	112 (70.0%)
Age, mean (sd)	85.29 (7.0)	84.8 (7.1)	60.4 (13.6)
Race, n(%)			
White	224 (72.7%)	123 (76.9%)	119 (74.4%)
Black/African American	70 (22.7%)	30 (18.8%)	29 (18.1%)
Other[a]	14 (4.5%)	7 (4.4%)	12 (7.5%)
Hispanic, n(%)			
Yes	13 (4.2%)	5 (3.1%)	14 (8.7%)
No	295 (95.8%)	155 (96.9%)	146 (91.3%)
Education, n(%)			
No degree	174 (56.5%)	87 (54.4%)	20 (12.5%)
GED	10 (3.2%)	8 (5.0%)	not reported
High school diploma	97 (31.5%)	52 (32.5%)	91 (56.9%)
Bachelor's degree	16 (5.2%)	8 (5.0%)	22 (13.8%)
Graduate degree	11 (3.6%)	5 (3.1%)	27 (16.9%)
Marital status, n (sd)			
Married	78 (25.3%)	46 (28.8%)	116 (72.5%)
Widowed	201 (65.3%)	106 (66.2%)	16 (10.0%)
Divorced	16 (5.2%)	4 (2.5%)	18 (11.2%)
Separated	3 (1.0%)	1 (0.6%)	1 (0.6%)
Never married	10 (3.2%)	3 (1.9%)	9 (5.6%)
Relationship of Caregiver to Person Living with ADRD, n(%)			
Child	n/a	30 (18.8%)	
Spouse	n/a	98 (61.3%)	
Other	n/a	32 (20.0%)	
Income[b], mean (sd, median)	2.70 (3.1, 1.7)	2.83 (2.7, 1.9)	not reported
MMSE, mean (sd)	14.34 (6.4)	13.52 (6.1)	not reported
Functional activity limitations, mean (sd)	0.57 (2.1)	7.7 (2.2)	not reported
Behavioral symptoms, mean (sd)	2.78 (2.4)	3.19 (2.6)	not reported
No. Chronic Conditions, mean (sd)	2.84 (1.5)	2.88 (1.5)	not reported
Community dwelling, n(%)	234 (76%)	125 (78.1%)	not reported
Caregiver lives with Person with ADRD, n(%)	n/a	77 (48.1%)	77 (48.1%)

[a] "Other" race includes: "American Indian or Alaska Native, Asian, and Native Hawaiian or Other Pacific Islander (per OMB standards)."
[b] Income reported as ratio of family income to federal poverty level.
ADRD = Alzheimer's Disease Related Dementias

TABLE 3.2: Average TTO-weights by Self-reported Health Status

	Full Sample (n=308)		Paired Sample (n=160)			
	TTO-weights People living with ADRD		TTO-weights People living with ADRD		TTO-weights Caregivers	
Self-reported Health Status	n (%)	Mean (sd)	n (%)	mean (sd)	n (%)	mean (sd)
Excellent	11 (3.6%)	0.87 (0.01)	6 (3.8%)	0.87 (0.01)	28 (17.5%)	0.92 (0.02)
Very Good	48 (15.6%)	0.83 (0.02)	24 (15.0%)	0.83 (0.02)	46 (28.8%)	0.88 (0.03)
Good	67 (21.8%)	0.78 (0.02)	41 (25.6%)	0.78 (0.02)	49 (30.6%)	0.83 (0.03)
Fair	91 (29.5%)	0.67 (0.01)	44 (27.5%)	0.66 (0.13)	33 (20.6%)	0.70 (0.02)
Poor	91 (29.5%)	0.47 (0.02)	45 (28.1%)	0.47 (0.02)	4 (2.5%)	0.51 (0.01)

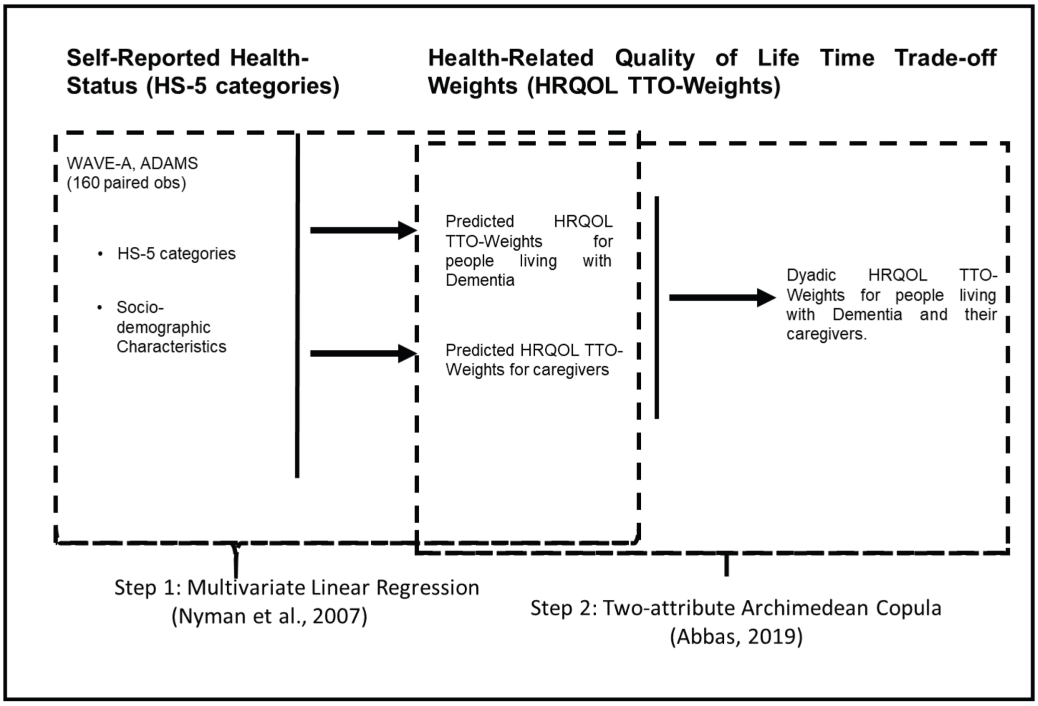
n = sample size
sd = standard deviation
TTO-weights = HRQOL Time Trade-off Weights
ADRD = Alzheimer's Disease Related Dementia

TABLE 3.3: Regression Models: Individual and Dyadic TTO-weights on Dementia Clinical Features

	TTO-weights			Dyadic TTO-weights
	People living with ADRD (n=308) Coefficient Estimate (95% CI)	People living with ADRD (n=160) Coefficient Estimate (95% CI)	Caregiver (n=160) Coefficient Estimate (95% CI)	(n=160) Coefficient Estimate (95% CI)
Intercept	0.665 (0.438, 0.894)***	0.670 (0.338, 0.986)***	0.944 (0.809, 1.075)***	0.778 (0.669, 0.886)***
People Living with ADRDs' Characteristics				
Number of behavioral symptoms	-0.003 (-0.010, 0.005)	-0.006 (-0.015, 0.004)	-0.006 (-0.012, -0.001)**	-0.004 (-0.007, -0.001)**
MMSE	0.000 (-0.003, 0.001)	-0.001 (-0.004, 0.005)	-0.001 (-0.004, 0.001)	-0.000 (-0.002, 0.001)
Functional activity limitations	-0.008 (-0.015, -0.001)*	-0.006 (-0.019, 0.006)	-0.001 (-0.005, 0.008)	-0.000 (-0.004, 0.003)
Place of Residence (ref= nursing home)	0.044 (0.003, 0.085)**	0.032 (0.025, 0.090)	-0.017 (-0.049, 0.016)	0.000 (-0.018, 0.018)
Age	-0.000 (-0.003, 0.002)	0.000 (-0.003, 0.004)	-	0.001 (-0.001, 0.002)
Gender (ref=Male)	-0.023 (-0.059, 0.014)	-0.041 (-0.093, 0.012)	-0.009 (-0.025, 0.008)	-0.009 (-0.025, 0.008)
Race (ref=White)				
Black/African American	-0.015 (-0.056, 0.027)	0.026 (-0.080, 0.133)	-	0.027 (-0.026, 0.081)
Other	-0.044 (-0.121, 0.033)	-0.054 (-0.166, 0.058)	-	-0.005 (-0.053, 0.043)
Education (ref=No degree)				
GED	0.038 (-0.053, 0.129)	0.027 (-0.078, 0.131)	-	0.009 (-0.024, 0.042)
High school diploma	0.042 (0.006, 0.079)**	0.047 (-0.007, 0.100)	-	0.017 (-0.004, 0.035)
Bachelor's degree	0.052 (-0.110, 0.214)	0.060 (-0.110, 0.267)	-	0.030 (-0.052, 0.020)
Graduate degree	0.091 (0.005, 0.178)*	0.100 (-0.032, 0.232)	-	0.031 (-0.011, 0.073)
Marital Status (ref=Married)				
Widowed	0.064 (0.022, 0.105)**	0.056 (0.001, 0.113)*	-	0.000 (-0.025, 0.026)
Divorced	0.060 (-0.017, 0.138)	0.110 (-0.047, 0.267)	-	0.027 (-0.025, 0.079)
Separated	0.052 (-0.110, 0.214)	0.187 (-0.104, 0.478)	-	-0.012 (-0.104, 0.079)
Never Married	0.044 (-0.050, 0.139)	0.095 (-0.080, 0.270)	-	-0.012 (-0.048, 0.073)
Caregivers' Characteristics				
Age	-	-	-0.002 (-0.003, -0.001)***	-0.002 (-0.002, -0.001)***
Gender (ref=Male)	-	-	-0.001 (-0.030, 0.028)	-0.006 (-0.023, 0.010)
Race (ref=White)				
Black/African American	-	-	-0.014 (-0.051, 0.024)	-0.022 (-0.077, 0.032)
Other	-	-	-0.050 (-0.101, 0.001)*	-0.023 (-0.058, 0.012)
Education (ref=No degree)				
GED[a]	-	-	Not reported	Not reported
High school diploma	-	-	0.017 (-0.025, 0.060)	0.009 (-0.015, 0.034)
Bachelor's degree	-	-	0.068 (0.016, 0.120)**	0.039 (-0.008, 0.069)*
Graduate degree	-	-	0.088 (0.035, 0.140)***	0.055 (0.022, 0.089)**
Marital Status (ref=Married)				
Widowed	-	-	-0.041 (-0.090, 0.007)	0.001 (-0.026, 0.028)
Divorced	-	-	-0.034 (-0.075, 0.007)	-0.011 (-0.034, 0.011)
Separated	-	-	0.016 (-0.149, 0.181)	0.030 (-0.076, 0.135)
Never Married	-	-	-0.001 (-0.058, 0.056)	-0.013 (-0.044, 0.018)
Relationship to person living with ADRD (ref=spouse)				
Child	-	-	0.037 (-0.007, 0.082)	0.003 (-0.032, 0.039)
Other	-	-	0.051 (0.002, 0.100)*	0.012 (-0.025, 0.048)

[a] GED was not reported for care partners in ADAMS.
TTO-weights = HRQOL Time Trade-off Weights
ADRD = Alzheimer's Disease Related Dementias
GED = Graduate Equivalency Degree
* p<0.1; ** p<0.05; *** p<0.001

3.7 Figures



The figure illustrates the 2-step process followed to obtain the dyadic TTO-weights. Step 1 involves the prediction of two sets of TTO-weights using a paired sample from WAVE-A of the Aging Demographics and Dementia Survey (ADAMS) and the linear models published by (Nyman et al.,2007). Step 2 involves using the two sets of predicted TTO-weights and a two-attribute Archimedean utility copula model proposed by (Abbas and Sun, 2019).

FIGURE 3.1: Two-step Mapping from Health-Status Categories to Dyadic TTO-Weights

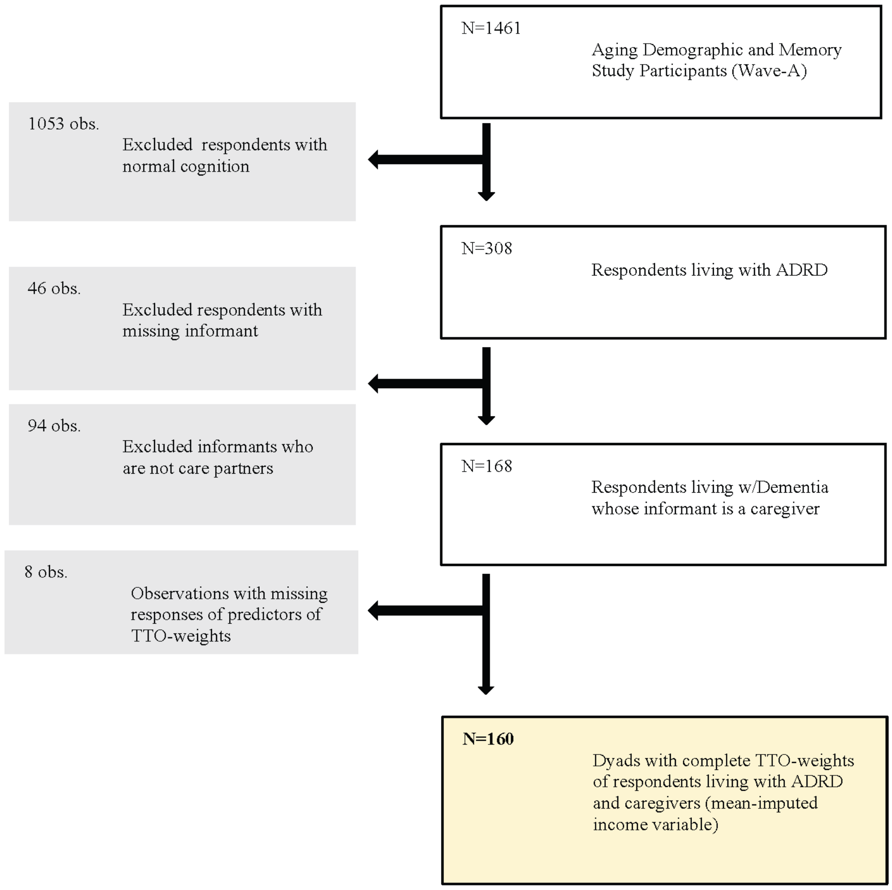


FIGURE 3.2: Analytic Sample from the Aging, Demographics, and Memory Study (ADAMS) Participants

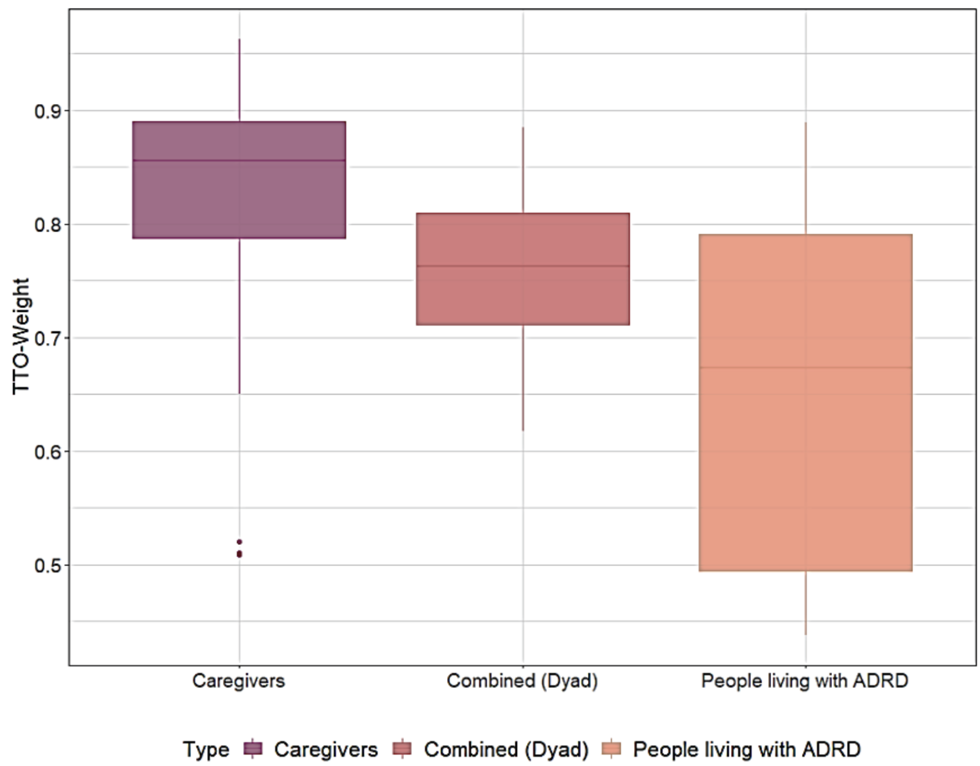


FIGURE 3.3: Interquartile Range of estimated Individual TTO-wights of People living with ADRD and Caregivers versus Dyadic TTO-weights (paired sample, $n = 160$)

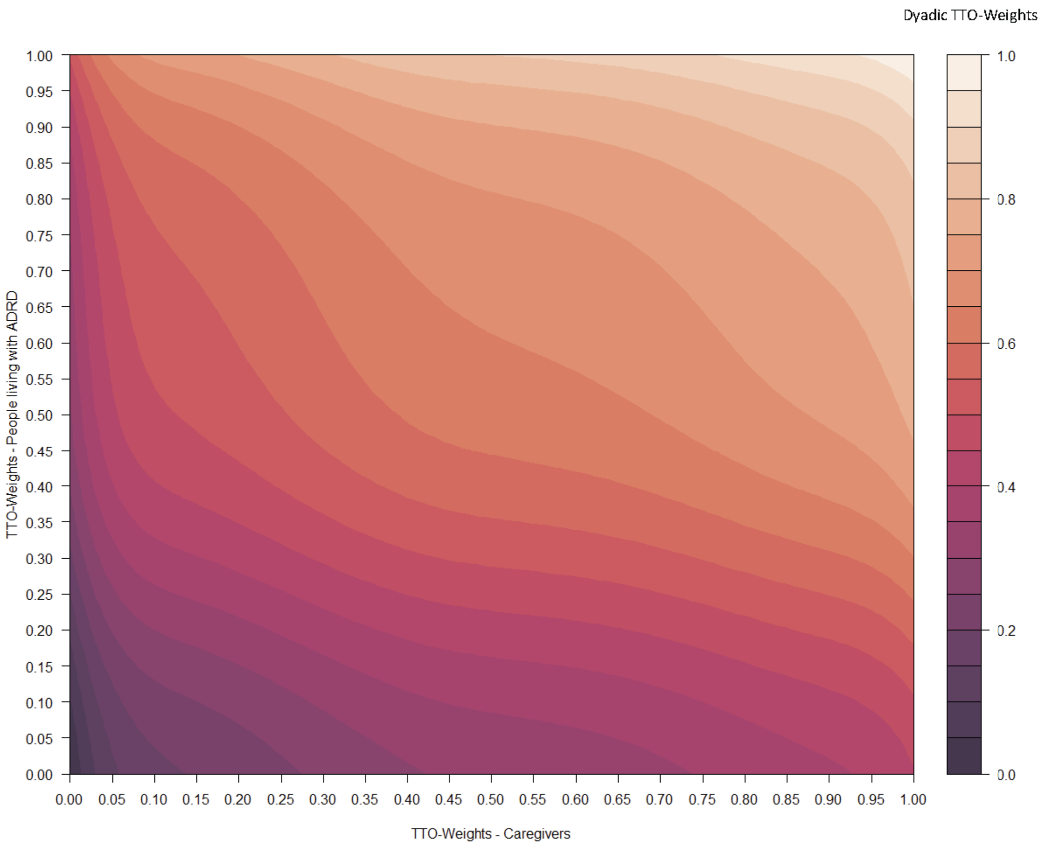


FIGURE 3.4: Iso-value Contour Lines of Dyadic TTO-weights

Chapter 4

Cost-Effectiveness Analysis of Interventions that increase Time in the Community among Medicare Beneficiaries living with Dementia

Abstract

Purpose Many people living with dementia would prefer to age at home and receive care within their communities but often experience unmet care needs that lead to preventable emergency room (ER) visits, hospital readmissions, and mortality. Non-pharmacological interventions can prolong time spent at home by reducing the number of transitions out of the community, yet their cost-effectiveness remains unclear. We evaluate interventions that increase time at home by reducing transitions from community to the nursing home, 30-day ER readmissions or hospital readmissions, as well as composite strategies that reduce two or three transitions out of the community. **Methods:** We developed a novel discrete event system simulation of community-dwelling dementia-diagnosed Medicare beneficiaries over a lifetime time horizon. For 24 strata (incident age, sex, race) we simulate sequences of transitions across 10 settings of care including community, NH, ER, and hospital settings, the number of cumulative chronic health conditions over time, care costs, and mortality. Time-dependent transition intensities and care costs, as well as models of chronic conditions were fitted to Medicare claims and nursing home Minimum Data Set (MDS) assessments for years 2011-2020. The treatment effects of interventions were extracted from published literature and modeled assuming proportional hazards over 18 months. Across interventions/strategies we compare average 30-day ER and hospital readmissions, NH admissions, length of stay (LoS) in the community, and total time gained in the community relative to standard of care, running $50,000$ trajectories for each scenario. In cost-effectiveness analysis, we calculate ICERs as the incremental cost per year gained in the community and as the incremental cost per quality adjusted life year (QALY). **Results:** Reducing 30-day ER readmissions is the only effective intervention in increasing average LoS in the community (169.0 days, SE(1.784)) compared to standard of care (157.7 days, SE(1.784)). Except for the composite intervention that reduces nursing home admissions and 30-day hospital readmissions, all composite strategies increase average LoS in the community with the strategy the reduces nursing home admissions and 30-day ER readmission being the most effective (173.0 days SE(1.875)). On average, the highest incremental total years in the community is achieved by the composite strategy that reduces nursing home admissions, 30-day ER and hospital readmissions increasing 0.34 years (122.7 days) relative to standard of care. Reducing 30-day hospital readmissions only or reducing nursing home admissions and 30-day hospital readmissions, did not increase total years in the community. From a health care payer's perspective, the intervention that reduces 30-day ER readmissions as well as the composite strategy that simultaneously reduces 30-day ER and hospital readmissions are cost saving relative to standard of care. The intervention that reduces 30-day hospital readmissions and the composite strategy that reduces 30-day hospital readmissions are dominated by standard of care. **Conclusion:** Reducing 30-day ER readmissions is a cost saving alternative to prolong time in the community for people living with dementia. Additional gains in prolonging time in the community for people living with dementia are possible by implementing composite interventions that complement the benefits of reducing nursing home admissions or reducing hospital readmissions in a cost-effective way.

4.1 Introduction

Dementia affects more than 6 million Americans 65 years and older (Alz-Association, 2023). People living with dementia are particularly vulnerable to receiving poor quality and uncoordinated care throughout their lifetimes that can affect their health outcomes, quality of life, and financial stability (NASEM, 2023; Nicholas et al., 2021; Nandi et al., 2024). At the same time, long-term care for people living with dementia constitutes a significant proportion of expenditures for the health system, people living with dementia, and their families; as people living with dementia typically require a higher number of care hours than their counterparts living without dementia (Jutkowitz et al., 2020; Patterson et al., 2023; Li et al., 2024; Keeney et al., 2020).

Most people living with dementia would prefer to age at home and receive care within their communities (NASEM, 2024). Transitional care interventions are designed to ease and support transitions between settings of care and can extend time spent at home (Hirschman and Hodgson, 2018). For example, the Money Follows the Person (MFP) Demonstration program (not dementia specific), enabled financial mechanisms to support voluntary transition of Medicaid eligible long-stay nursing home (NH) residents(≥90 days) back to their communities through increased access to home and community-based services (Medicare & Medicaid Services, n.d.). Robison et al. (2015), found that MFP had beneficial outcomes (increased quality of life and life satisfaction) for individuals who transitioned to the community and their family caregivers (lower levels of burden), as well as a reduced number of nursing home readmissions. Furthermore, Jutkowitz et al. (2023), found that non-pharmacological interventions that reduce transitions to nursing homes by providing people living dementia and their family caregivers, knowledge, skills and support to manage their care challenges are cost saving (i.e., increased benefits and reduced costs) from a societal perspective.

An important barrier to supporting people living with dementia to age at home is that they often experience disproportionately higher rates of falls, hospitalizations, emergency room visits, and mortality (Wysocki et al., 2014). People living with dementia discharged to their communities may still experience lower quality and coordination of care, which can lead to unanticipated transitions (Bellantonio et al., 2008). Individuals who participated in the Connecticut MFP, despite having lower readmission rates to nursing homes, also experienced higher falls rates and more frequent visits to the hospital and emergency department (Robison et al., 2020; Marrero et al., 2019), as well as higher mortality rates after their transition to home (Irvin et al., 2017). Similarly, Takahashi et al. (2021) report results of a randomized trial that evaluated participants in the Mayo Clinic Care Transitions Program (MCCT), an intervention designed to support those discharged from skilled nursing facilities to their homes. MCCT participants had higher rates of emergency department visits and hospitalization at 180 days than the comparison group, suggesting that participants still encountered important unmet care needs within their communities (Takahashi et al., 2021).

For payers and policy makers to include transitional care interventions into their planning, they need clear evidence on the trade-offs and long-term implications of reimbursing transitional care interventions for the population with dementia. Yet, the risk of adverse events (e.g., falls) and preventable use of health services (e.g., preventable hospitalization, emergency room visits) after transitioning to the community remains understudied(Groenvynck et al., 2022). More importantly, only few transitional care interventions have been successful in all desired outcomes that support people living with dementia to age at home (NASEM, 2024). Comprehensive interventions that address various care needs simultaneously are possible; however, a fragmented and disjointed health-care system, coupled with misaligned and conflicting financial incentives, restricts the ability of health care providers to test and implement interventions whose outcomes fall outside what can be reimbursed directly to them. Consequently, the potential benefits of implementing multidimensional and comprehensive interventions for people with dementia to remain in their community are not well understood (NASEM, 2024; NASEM, 2021b).

To address these issues, we developed a novel individual-level stochastic simulation of community-dwelling dementia-diagnosed Medicare beneficiaries as they age and transition between 10 different settings of care throughout their lifetimes after dementia diagnosis. We also model the associated cost from Medicare's perspective to provide care for this population over their lifetimes and across care settings. We evaluated the comparative effectiveness and cost-effectiveness of interventions that increase time in the community by reducing transitions from the community to the nursing home (C-NH), 30-day ER readmissions (ER-C-ER) or hospital readmissions (H-C-H), as well as composite strategies that reduce two or three transitions out of the community simultaneously.

4.2 Methods

Analytical Cohort from Residential History File

We use data from the Residential History File (RHF) to estimate transition rates between care settings, the rates at which Medicare beneficiaries accumulate chronic health conditions, and the associated care costs reimbursed by Medicare. The RHF is a data repository that summarizes information from Medicare claims and nursing home minimum data set (MDS) assessments that provide the place and time at which health services were provided, including stays in non-Medicare-paid nursing homes (Intrator et al., 2011). With the information that the RHF provides, we construct a calendar of the timing (e.g. calendar time) and sequence of locations of care (e.g., hospital, nursing home, emergency room), allowing us to characterize the transition rates and types of care transitions that Medicare beneficiaries experience throughout their lifetimes.

For this study, we defined an analytical cohort from RHF by identifying beneficiaries diagnosed with dementia in 2011 65 years of age or older. The diagnosis of dementia and chronic health conditions is based on the information available in claims (Warehouse, n.d.). We tracked the sequence of health care locations visited by people in the analytical cohort over 9 years (2011 and 2020) using a random sample of 5% of all available Medicare claims (sample size = 9,232 beneficiaries diagnosed with dementia in 2011).

4.2.1 Statistical Models

Synthetic Baseline Characteristics

To accurately represent the marginal and joint distributions of the attributes of the analytical cohort in the simulation, we follow a vine-copula modeling approach. Vine copulas model a joint density of k variables $f(x_1, x_2, ..., x_k)$, by factorizing it into a product of $\binom{k}{2}$ bivariate copula densities and k marginal densities (Joe and Kurowicka, 2011; Czado and Nagler, 2022). With this approach, we simulate a synthetic cohort of Medicare beneficiaries diagnosed with dementia with characteristics that reflect the distribution of characteristics and the correlation structure observed in the analytical cohort. (Appendix C)

First, we fit a categorical distribution to the distribution of three mutually exclusive racial groups (Black, White, or Other/Unknown) in the analytic sample. Second, within each race category we fit a three-dimensional vine copula representing the conditional density of incident age of dementia, the number of chronic health conditions, and sex (Female/Male). In the simulation, we draw samples from the joint distribution of the 4 baseline characteristics following the factorization in equation 4.1:

$$f(x_1, x_2, x_3, x_4) = f(x_1, x_2, x_3|x_4) * f(x_4) \tag{4.1}$$

where:

1. x_1: sex(female/male),
2. x_2: dementia incident-age(years)
3. x_3: number of chronic health conditions
4. x_4: race(black/white/other)

The structure of the vine copula of the conditional densities of the 3 baseline characteristics within each Race category is illustrated in Appendix C. We used the package "VineCopula" (Schepsmeier et al., 2020) in the R programming language to estimate the vine copulas from the data and to simulate sets of baseline characteristics in the simulation model.

Stratification

We stratify the cumulative chronic disease model and the trajectories of care model based on the levels of three sociodemographic characteristics at baseline: dementia incident age (65-74, 75-84, 95+), sex (female,male), and race (black, white, other); i.e., 24 strata in total.

Model of Cumulative Chronic Conditions

The cumulative number of chronic health conditions is a critical determinant of the health status of the elderly. It is correlated with the risk of hospitalizations, ER visits, and death (Bishop, Haas, and Quiñones, 2022; Buttorff, Ruder, and Bauman, 2017). To model this process, we fit data from the analytical sample in the following way: First, we define the dependent variable as the change in the cumulative number of chronic health conditions experienced by a person during a stay in a specific setting of care, i.e., we model the count of incident cases of chronic health conditions during the time interval between settings of care. We regress the dependent variable to four potential covariates: a) setting of care currently in, b) number of chronic health conditions at baseline, c) number of chronic health conditions at exit of the previous setting of care, and d) age at the start of the current stay.

To select the best fit model for each strata, we first define three candidate groups of models based on the distributional assumptions of the counts: a) Poisson, b) negative binomial(modeling over-dispersion), and b) hurdle model(modeling excess zeros), which is a two-component model with a truncated count component for positive counts and a hurdle component that models the zero counts(Hilbe, 2011; Mullahy, 1986). Within each group of models, we select the best-fit model among three nested covariate specifications and select the best-fit model among the three remaining candidate models. The goodness of fit criteria that we used to select the best-fit model in each step is the Aikake Information Criterion(AIC). The online-Appendix (not in this document) details the specification of the nine candidate models for each strata. The model(s) were estimated using packages 'stats' (poisson), 'MASS' (negative binomial), and 'pscl' (hurdle) in the R programming language (Venables and Ripley, 2002; Jackman, 2020)

Model of Trajectories of Care

To model the individual trajectories of care we develop a model of a continuous-time stochastic process over a discrete and finite state space. The model is formulated as a system of cause-specific intensity functions (also known as hazard functions in survival analysis) that describe the instantaneous rates at which a person would transition from a state r, to a state s, $r \neq s$. In our study, the set of states a person can transit "into" and "out" of is a finite number of settings of care plus an additional state that characterizes the event of end of life(dead state).

Let $\mathbb{S}$ denote the set of possible settings of care that a person can visit throughout their life after dementia diagnosis.

$$\begin{aligned}\mathbb{S} =[&Community,\ Home\ Health\ Assistance(HHA),\\ &Skilled\ Nursing\ Facility(SNF),\ Nursing\ Home(NH),\\ &Emergency\ Room(ER),\ Observation,\\ &Inpatient,\ Inpatient\ Other,\\ &Long-term\ Care\ hospital(LTCH),\\ &Inpatient\ Rehabilitation\ Facility(IRF),\ Dead]\end{aligned}$$

Since $\mathbb{S}$ contains ten possible settings of care and one absorbing state (dead), there are 100 possible transitions between pairs of states in $\mathbb{S}$. Figure 3.2 in Appendix C contains the transition diagram of the 10 settings of care.

Let $X_t \in \mathbb{S}$, $t \leq 0$, be a collection of random variables indexed by time that can only take values from the set $\mathbb{S}$. Consider an individual at time t who is in setting $X_t = r,\ t \geq 0$, the intensity or infinitesimal probability ($\delta \to 0$) of transitioning to the next state $X_{t+\delta} = s$ is represented by the function $\lambda_{r,s}(t, \mathbf{z}(t), \mathcal{F}_t)$:

$$\begin{aligned}&\lambda_{r,s}(t,\mathbf{z}(t),\mathcal{F}_t) = lim_{\delta\to 0}\frac{\mathbb{P}\Big[X_{t+\delta} = s|X_t = r, \mathbf{z}(t), \mathcal{F}_t\Big]}{\delta}\\ &for\ r,s = 1,...,|\mathbb{S}|\end{aligned} \tag{4.2}$$

Where $\lambda_{r,s}$ may depend on time t, covariates $\mathbf{z}(t)$, and the history of settings of care visited up to time t, namely $\mathcal{F}_t = \{X_{t_0}, X_t, ..., X_{t-1}\}$.

Additionally, let the random variable T_n denote the n^{th} event time, i.e., the time at which any transition between states occurs, and the random variable $\tau = (T_n - T_{n-1})$ denote time increments or inter-arrival times between states. We denote the associated distribution function of τ as $F(\tau)_{r,s}$. We index the distributions of inter-arrival times by the origin and destination states to highlight that the inter-arrival times between each pair of distinct settings may follow different distributions. Finally, let $\Lambda_{r,s}(t,\mathbf{z}(t),\mathcal{F}_t) = \int_0^t \lambda_{r,s}(u,\mathbf{z}(u),\mathcal{F}_t)du$ denote the cumulative intensity function that describes the rate of transition between state r and state s, as well as its associated inverse function $\Lambda^{-}_{r,s}(t, \mathbf{z}(t), \mathcal{F}_t)$.

Since the intensity functions for transition rates between settings of care are allowed to be non-constant and depend on time-varying covariates with respect to global time of the process (age and cumulative chronic health conditions), the stochastic process in equation (2.2) is non-Markovian. In this formulation, the inter-arrival time $\tau = (T_s - T_r)$ between setting of care r and setting of care s has distribution function $F_{r,s}$ which can be non-exponential.

For each of the 24 strata, we estimate 100 intensity models for the 100 transitions. For each transition, we select the model with the best fit based on AIC, among 20 candidate models: four candidate parametric models (weibull, exponential, gamma, or log-normal) and six candidate flexible parametric models (2, 3, or 5 internal knots, in the odds or hazard scale). We also compare adjusted and unadjusted specifications of the parametric and flexible parametric models. The covariate set used for adjustment includes the number of chronic health conditions at the beginning of each episode of care and age (years). We model covariate effects following a proportional hazards or proportional odds specification. The online-Appendix contains the dictionary of the 2,400 best-fit intensity models and their specification. We use the 'flexsurv' R package (Jackson, 2016) to estimate the set of intensity functions as a multi-state model, and the R package 'nhppp' (Trikalinos and Sereda, 2024) to sample inter-arrival times for each transition based on the set of intensity functions we estimated.

Models of Costs of Care

We link the RHF analytic sample with the cost and use segment of the master beneficiary summary file (MBSF) (Research Data Assistance Center (ResDAC), n.d.) to estimate longitudinal models of care costs in each type of care setting that Medicare reimburses. We consider skilled nursing facility stays, hospital stays, other Inpatient stays (e.g., Long-term care Hospital, Inpatient Rehabilitation Facility, Inpatient Psychiatric Facility), ER visits that lead to an inpatient stay, ER visits that do not lead to an inpatient stay, and home-health assistance visits. For each type of Medicare reimbursed cost, we fit longitudinal generalized gamma regressions (with logistic link function) to account for nonnegative and skewed data (Manning, Basu, and Mullahy, 2005). We adjusted for incident age, sex, race, and cumulative chronic health conditions and compared goodness of fit for linear, quadratic, and cubic time trends using AIC and BIC.

Since Medicare does not cover nursing home stays, we estimate a longitudinal binary logistic regression to model the probability of Medicare beneficiaries to be dually eligible to receive Medicaid and Medicare benefits as a function of incident age, sex, race, cumulative chronic health conditions and time. We use a restricted cubic spline with logarithmic transformed time and tested goodness of fit for different numbers of knots using AIC and BIC. We use R package 'rms' (Harrell Jr, 2024).

In the simulation, beneficiaries who are predicted to be dually eligible and experience a nursing home stay are assigned a cost per day as reported in the literature (Bharmal et al., 2012; Kaiser Family Foundation, 2024). For observation episodes in the ER (not reported in the MBSF) we assign a cost per visit based on Burke et al.(2020).

Models of HRQOL

There is limited evidence and data linking preference-based measures of health-related quality of life weights with the settings at which people with dementia receive care, and are typically reported only based on the person's stage of dementia. Given these limitations, we integrate the health-related quality of life weights (hrqol weights) for individuals with dementia into the simulation using the following assumptions and steps.

First, we consider the progression of the cumulative number of chronic health conditions over time as a proxy of declining health status and the worsening dementia stage of people living with dementia, since a time-varying comorbidity burden, more than a baseline comorbidity burden, has been found to be associated with cognitive decline (Haaksma et al., 2017; MacNeil-Vroomen et al., 2020). Based on this evidence, we categorize in three levels the number of cumulative chronic health conditions that a person living with dementia experiences. Consequently, we assign hrqol weights to each person living with dementia assuming that on average people living with dementia in the low burden category (0-3 cumulative chronic health conditions) have a high chance of being in a mild stage of dementia, people living with dementia in the medium burden category (4-8 cumulative chronic health conditions) have a high chance of being in a moderate stage of dementia, and finally people living with dementia in the high burden category (8-12 cumulative chronic health conditions) have a high chance of being in the severe stage of dementia.

We also assume that, on average, people living with dementia and living in nursing homes experience a lower quality of life compared to those living in the community and that the rate at which hrqol decreases as dementia progresses varies according to the care setting (Jutkowitz et al., 2023). Finally, we assume that people living with dementia who receive care in similar settings of care experience similar levels of hrqol (e.g., nursing homes and skilled nursing facilities), as well as similar rates of decline over time of their hrqol. (Appendix C)

4.2.2 Discrete Event Simulation

Structure

The simulation model utilizes the five previously described components (model of joint distribution of baseline characteristics, model of the counting process of chronic health conditions, multi-state model of trajectories of care, models of cost and hrqol) and is structured as a discrete event system (DES)(Banks et al., 2005; Cassandras, 1993).

Evolution of the process

The DES approach is appropriate for simulating dynamics that evolve over a finite discrete state-space in continuous time. In a DES the process evolves at unequal time intervals(jumps) at which transitions occur between states, a feature that can reduce computation time relative to other computational representations under which it is necessary to compute the state of the system at all points over a grid of time (Graves et al., 2021).

The algorithm we use to evolve the process in our simulation makes use of strata-specific transition intensity matrices Q_j, $j = 1, ..., 24$ that we estimated using the analytic cohort sample. At baseline ($t = 0$), every person in the dementia incident cohort in the simulation starts in the community ($X(t = 0) = Community$). To determine the next transition for each person, we first determine the set of possible states ($s \in \mathbb{S}$) that a person can transition to while being in the community, as well as the corresponding transition intensity functions, $\vec{\lambda}_{r=Community,s}$ that describe the transition rates from the community to each state in s. For clarity, we omit here indices for observations and strata. Second, we compute the cumulative intensity functions $\vec{\Lambda}_{r=Community,s}$ and approximate the corresponding inverse cumulative intensity functions $\vec{\Lambda}^{-}_{r=Community,s}$. Third, we sample a set of latent inter-arrival times $\vec{\tau}_{r=Community,s}$ via the inversion method (see the next section) and select the minimum inter-arrival time $\tau^{*}_{r=Community,s}$ among elements of $\vec{\tau}_{r=Community,s}$; i.e.,:

$$\tau^{*}_{r=Community,s} = min(\tau_{r=Community,1}, \tau_{r=Community,2}, \ldots, \tau_{r=Community,|s|})$$

With the inter-arrival time $\tau^*_{r=Community,s}$, we update the current state for each person in the community to the next state, determined by the second index of $\tau^*_{r=Community,s}$. Finally, the global simulation time for each person is updated to $(t_0 + \tau^*_{r=Community,s})$.

For transitions between states after the first, the steps are almost identical but differ in that now each person in the simulation is currently at any of the states in $\mathbb{S}$ except for the state they previously visited. After the first transition, we determine the sets of possible states to which each person can transition depending on which state they are currently at, as well as the corresponding transition intensity functions to those states. This task is now more costly because we have to determine the set of possible transitions for each person; however, by using an adjacency matrix or adjacency table, we can efficiently track the set of possible transitions for each person at all times. All the steps that follow are as described for the first transition. We compute cumulative intensities and their inverse functions, sample latent inter-arrival times, determine the next transition based on $\tau^*_{r,s}$, and update the current state and global time accordingly. The simulation repeats these steps until all people have died, but other stopping criteria are possible. An algorithmic representation of these steps, as well as a list and description of all parameters of the simulation model, can be consulted in Appendix C.

Sampling Inter-arrival Times

The inverse method relies on the fact that monotone transformations of the time dimension of a non-homogeneous Poisson point process yield another non-homogeneous Poisson point process (Cinlar, 2013; Trikalinos and Sereda, 2024).If the transformation is chosen to be the cumulative intensity function, then the new process (i.e., time-transformed process) is a homogeneous Poisson point process with rate one, from which we can obtain fast samples of the inter-arrival times.

4.3 Strategies of Transitional Care Interventions

Transition of Care Levers

We prioritize dementia interventions that act on transitions out of home and community-based care and identified from the literature three interventions for which there is evidence of an effect on at least one transition out of the community. (Table 4.1)

We denote as lever (1), interventions that reduce transitions from the community to a nursing home (C-NH). For this lever, we identified the Alzheimer's and Dementia Care (ADC) program. The ADC program is integrated within a healthcare system and offers people living with dementia and their caregivers a needs assessment, personalized care plans, and 24/7 access to a care manager. The ADC program was assessed using a case-control design with a matched sample of 1,083 participants receiving the intervention and a comparison group of 2,166 individuals with dementia. The primary outcome measured was the time to nursing home placement over a period of 3 years (Jennings et al., 2019).

Lever (2) denotes interventions that reduce 30-day ER readmissions. For this lever, we identified a modified version of the Care Transition Intervention (CTI) tailored for post-ER discharge to the community. The intervention involved a single home visit within 24 to 72 hours after ER discharge, followed by one to three phone calls from a paramedic coach over the following four weeks. During home visits, paramedics used coaching techniques to help participants understand the four key self-management components of the CTI: outpatient follow-up, self-management of medications, recognition of red flag symptoms and use of a personal health record. This adapted CTI was assessed through a preplanned subgroup analysis within a randomized controlled trial evaluating the effectiveness of CTI. The primary outcome was the readmission rate at 30 days to the emergency department (Shah et al., 2022).

For Lever (3) we focus on interventions aimed at reducing 30-day hospital readmissions. Although there are successful examples of interventions that reduce hospital readmissions at 30 days among elderly and high-risk patients, we did not identify an intervention with a similar impact that specifically targeted people living with dementia. Instead, for this lever, we use the findings of a retrospective cohort study of community-dwelling dementia patients, which assessed the link between high primary care continuity and potentially avoidable 30-day hospital readmissions (Godard-Sebillotte et al., 2021)

Composite Strategies

To examine the hypothesis that integrating more than one lever into a composite strategy to reduce multiple transitions out of the community can offer additional gains in extending time at home for people living with dementia, we also assess hypothetical composite strategies. These composite strategies are combinations of the three interventions described above (Levers 1, 2, and 3). We evaluate three two-lever composite strategies (levers 1 and 2, levers 1 and 3, levers 2 and 3) and one composite strategy that incorporates all three levers. The submodel with the relevant set of transitions affected by transitional care levers and composite strategies are illustrated in Figure 4.1.

Effect of Transitional Care Strategies

The effect of interventions and the joint effect of composite strategies in reducing transitions out of the community are modeled under proportional hazards. This means that the effect of interventions scales the corresponding baseline intensities (baseline hazards) by a constant factor relative to not receiving the intervention.

To illustrate this, consider lever (1) that only acts on the rate of transition from community-based care to the nursing home. Under proportional hazards, the intensity function for the i^{th} individual within the j^{th} strata that describes the transition from community-based care to nursing home is expressed as:

$$\lambda_j(t, z_i(g(t)), u_i)_{C,NH} = \lambda_0(t;\theta_j)_{C,NH}\, e^{\left(\beta\, z_i(g(t)) + \gamma u_i\right)} \tag{4.3}$$

Where $\lambda_0(t;\theta_j)_{C,NH}$ is the baseline hazard function which can belong to any of the parametric models or flexible parametric models considered, and is parameterized by the vector θ; β is a vector of time-fixed covariate effects; $z(g(t))$ is a vector of time-varying covariates and $g(t)$ is a function of time with respect to global time t; γ is a time-fixed scalar treatment effect; and u is an indicator of receiving the intervention.

Now consider a composite strategy that acts on transition of care levers (1) and (2), that is, the transition from community-based care to the ER given a discharge from the ER to the community and the transition from community-based care to nursing home. In this case, the effect of this composite strategy is represented by the vector $\vec{\gamma} = [\gamma_1, \gamma_2]$. The corresponding intensity functions for these transitions under strategy (2) are:

$$\lambda_j(t, z_i(g(t)), u_i, X(T_{n-1}) = ER)_{C,ER} = \lambda_0(t;\theta_j)_{C,NH}\, e^{\left(\beta\, z_i(g(t)) + \gamma_1 u_i\right)} \tag{4.4}$$

$$\lambda_j(t, z_i(g(t)), u_i)_{C,NH} = \lambda_0(t;\theta_j)_{C,NH}\, e^{\left(\beta\, z_i(g(t)) + \gamma_2 u_i\right)} \tag{4.5}$$

Where the indices C ,NH, and ER denote community, nursing home, and emergency room, respectively.

Two things should be noted from this representation. First, to model the effect of interventions that reduce 30-day ER readmissions, we incorporate one degree of state dependence to the intensity function $\lambda_j(t, z_i(g(t)), x_i, X_{T-1} = ER)_{C,ER}$, where $(X(T_{n-1}) = ER)$ denotes that the state in the previous event-time (T_{n-1}) was the ER. Under no intervention, state-dependency is not included. The same approach is used for strategies that reduce 30-day hospital readmissions since treatment assignment also depends on being previously discharged from the hospital to the community. Second, since we fit intensity functions for each of the 24 strata, the baseline hazards, $\lambda_0(t; \theta_j)$, are strata specific. This approach allows for incorporation of strata-specific treatment effects of the interventions and strategies; however, in this study, we will assume that the treatment effect(s) under each intervention and strategy are common across all strata.

Cost of Strategies

We assign to each intervention a cost of implementation per person per month. The intervention that affects transition rates from the community to nursing homes, ADC, costs \$106.00 usd per month as reported in the literature(Jennings et al., 2019). For interventions that reduce 30-day emergency department and hospital readmissions, the costs per person per month are not reported. For these interventions, we used study data on the type and number of personnel needed to deliver each intervention and estimated the cost per person per month. For the modified CTI intervention that reduces 30-day ER readmissions we calculate that the cost per person per month is \$247.00 usd, and for the hypothetical intervention that reduces 30-day hospital readmissions we estimate a cost per person per month of \$358.15 usd. For composite strategies, we assume that the costs of each of the one-lever interventions can be summed. (Appendix C)

Accessibility, Eligibility, and Duration of Treatment

We simulate treatment duration of 18 months for all interventions and composite strategies. Accessibility to treatment is assumed to be perfect for all individuals in the simulation, i.e., if a person is eligible, they receive the intervention. The eligibility criteria consists of being 65 years or older diagnosed with dementia and living in the community at any time during the 18 months of treatment duration. For interventions that reduce 30-day ER readmissions it is also necessary that the person living with dementia is discharged from the ER to the community to be eligible for the intervention. Similarly, for the intervention that reduces 30-day hospital readmissions it is necessary that the person living with dementia is discharged from the hospital to the community to be eligible. For composite strategies, the eligibility criteria combine the criteria for the one-lever interventions that compose them. For example, a person under composite strategy (1 & 2), would be eligible if they were discharged from the ER to the community during the 18 months of treatment duration and would experience both effects, i.e. a reduction in intensity to transition to the nursing home and a reduction in intensity to revisit the ER in the 30 days post-discharge. If the same person had not visited the ER previously, but is receiving care in the community during the 18 months of treatment duration, under composite strategy (1 & 2) they would still experience the effect of reducing the intensity of transition to the nursing home. The same logic is applied to the other three composite interventions.

After each transition occurs, the simulation assesses the eligibility of a person to receive the intervention based on the previous setting of care, $X(T_{n-1})$; the current setting of care, $X(T_n)$; and the global time of the simulation, t. If the criteria are met, the corresponding intensity functions under treatment are used to draw latent transition times and determine the next setting of care.

Comparative Effectiveness and Cost-effectiveness Analysis.

Across interventions/strategies, we compare average 30-day ER and hospital readmissions, NH admissions, and length of stay (LoS) in the community. We simulate 50,000 trajectories for each intervention/strategy and the control scenario where no intervention is in place (standard of care).

For cost-effectiveness analysis, we adopt a health system perspective and run a competing choice analysis. We sort each intervention/strategy in increasing order of total lifetime cost and compute incremental cost-effectiveness ratios (ICER) for each intervention as the incremental expected discounted cost of care divided by the incremental expected discounted quality adjusted life years (QALYs) or as the incremental expected discounted cost of care divided by the incremental expected years in the community (natural units). We assume that the health care payer has the capacity to implement all composite strategies without incurring additional care costs (e.g., no cost to coordinate different health care providers). Under this assumption, we identify the cost-effectiveness frontier (CEAF), where the reference for incremental costs and benefits is the next-best alternative on the list of strategies sorted by increasing total costs. We applied a 3% annual discount rate to future care costs and QALYs.

4.4 Sensitivity and Uncertainty Analysis

In sensitivity analysis, we compare interventions / strategies with their own control comparison, i.e., each intervention is compared to standard of care. This analysis reflects situations where only one intervention/strategy is a feasible alternative. In addition, we conducted a one-way sensitivity analysis from a health system perspective by varying "optimistic" (would favor the intervention/strategy) or pessimistic (would favor standard of care) assumptions regarding the effectiveness of the interventions/strategies (Jutkowitz et al., 2023). This means that we evaluate (2) versions of each one-lever strategy, ($2^2 = 4$) versions of each two-lever strategy, and ($2^3 = 8$) versions of the three-lever strategy. In this study, we did not perform a structural sensitivity analysis on the treatment regimes (e.g., delayed treatment effects or residual effects after the intervention ended) nor a probabilistic sensitivity analysis to assess the effect of parameter uncertainty (e.g., uncertainty from the hrqol estimates used).

4.5 Results

Synthetic Cohort

Table 4.2 and Figure 4.2 compare baseline characteristics observed in the RHF analytic cohort versus baseline characteristics in the synthetic cohort generated by simulation (n = $5,000$ and $50,0000$). Comparison of pairwise correlations shows that the simulation captures correlations between pairs of baseline characteristics observed in the analytic cohort.

Cumulative Chronic Health Conditions over Time

Figure 4.3 overlays the interquartile range of the cumulative number of chronic health conditions over different time horizons observed in the analytic sample with the interquartile range of the cumulative number of chronic health conditions from the simulation (n = 50,000). At baseline, three, five, and ten years, the median, as well as the first and third quartiles of the distribution of cumulative chronic conditions observed in the analytic sample fall within the interquartile range of the model predictions.

Trajectories of Care: Length of Stay in each Setting of Care

Figure 4.4 overlays the interquartile range of the length of stay (days) in each setting of care observed in the analytic sample with the interquartile range of the length of stay (days) in each setting of care from the simulation (n = 50,000). The interquartile range of simulation predictions covers the range of the observed length of stay in each setting of care, in the analytical sample of the RHF.

4.5.1 Comparative Effectiveness of Transitional Care Interventions and Strategies

During the first 18 months (i.e., treatment duration), the composite strategy that reduces NH admissions, and 30-day hospital and ER readmissions is the most effective in increasing average LoS in the community (63.3 days SE(0.876)) compared to standard of care (61.2 days SE(0.811)), increasing the LoS by 2.1 additional days on average. Among one-lever strategies, the strategy that reduces 30-day ER admissions is the only strategy to increase average LoS in the community (62.3 days SE(0.854)) compared to standard of care, prolonging LoS in the commmunity by 0.6 additional days on average. (Table 4.3)

During a lifetime and among one-lever strategies, reducing 30-day ER readmissions is the only strategy that increases LoS in the community on average (170.0 days SE(1.784)). All composite strategies, except reducing NH admissions and 30-day hospital readmissions, increase average LoS in the community compared to standard of care. The two-lever composite strategy that reduces NH admissions and 30-day ER readmissions is the most effective (173.0 SE (1.877)), adding 15.3 days to the average LoS in the community compared to standard of care (157.7 days SE (1.480)). (Table 4.3)

4.5.2 Cost Effectiveness Analysis of Transitional Care Interventions and Strategies

Incremental Cost Effectiveness, ($/QALY)

From a healthcare payer perspective and over a lifetime time horizon, the intervention that reduces 30-day ER readmissions and the composite strategy that reduces 30-day ER and hospital readmissions are cost-saving, that is, these interventions increase QALYs and cost less relative to standard of care. The composite strategy that reduces nursing home admissions and 30-day ER readmissions and the composite strategy that reduces nursing home admissions and 30-day ER and hospital readmissions were both more effective than cost-saving interventions / strategies, but also cost more. (Table 4.4) These four interventions/strategies are the only ones that are potentially cost-effective, since they are the only alternatives that lie on the cost-effectiveness frontier. All other interventions/strategies are dominated. (Figure 4.5)

Incremental Cost Effectiveness, ($/Year in the Community)

When we consider benefits in the natural unit of years gained in the Community, the intervention that reduces 30-day ER readmissions and the composite strategy that reduces 30-day ER and hospital readmissions remain as cost-saving alternatives. The composite strategy that reduces nursing home admissions and 30-day ER and hospital readmissions is more effective than cost-saving interventions/strategies, but also costs more. (Table 4.5)These three interventions/strategies lie on the cost-effectiveness frontier, while all other interventions are dominated. (Figure 4.6)

Sensitivity Analysis

The intervention that only reduces 30-day hospital readmissions and the composite strategy that reduces nursing home admissions and 30-day hospital readmissions are dominated by standard of care, since they cost more and reduce years in the community or QALYs. The intervention that reduces nursing home admissions increased 0.02 years in the community and 0.003 QALYs relative to standard of care, and increases lifetime costs by $\$3,688.0$. The composite strategy that reduces nursing home admissions and 30-day ER readmissions yields an additional 0.24 years in the community and 0.12 QALYs, as well as additional lifetime costs of $159.59. The composite intervention that reduces nursing home admissions, and 30-day ER and Hospital readmissions achieves the most benefits, adding 0.34 years in the community and 0.126 QALYs, and increasing lifetime costs by $\$1,739.23$. (Table C.3 in Appendix C) After varying the effectiveness of treatment in one-way sensitivity analysis, the results did not change. (Table C.4 in Appendix C)

4.6 Discussion

In this study, we model care trajectories that represent the experience of Medicare beneficiaries diagnosed with dementia as they age and transition between different settings of care after being diagnosed, as well as the associated costs that Medicare has to reimburse for providing care to this population. Using this model, we evaluated evidence-informed interventions that can reduce transitions out of home and community-based care by successfully supporting people living with dementia and their family caregivers in meeting their care needs within their communities.

Our contribution is twofold. First, we provide novel evidence comparing the reimbursement implications and benefits of three existing interventions that are delivered in different settings of care, something that is only possible by recognizing the multiple pathways through which a person living with dementia may end up receiving care outside of their community. Second, we provide the first evidence on the benefits of four more ambitious (but still hypothetical) interventions that simultaneously address two or three of these pathways, underscoring the potential value of leveraging the complementarities inherent in existing interventions.

Adopting a health care payer perspective, the three existing interventions we evaluated had modest or no benefits in prolonging time in the community and quality of life compared to standard of care. With exception of reducing 30-day ER readmissions, which reduces lifetime care costs, the other two interventions increased lifetime care costs by different magnitudes and are dominated. The intervention that reduces nursing home admissions had the highest lifetime cost increase, as it is the only intervention of the three that provides long-term support, while the other two provide intermittent support limited to one month after discharge from the ER or the hospital. Considering the four composite interventions that reduce two or three transitions out of the community, our analysis shows that the strategy that reduces 30-day ER and hospital readmission is cost-saving (increase time in the community and QALYs, as well as reduce lifetime care costs). The composite intervention that reduces nursing home admission and ER and hospital readmission is the most effective but the second most costly compared to standard of care (but still potentially cost-effective), while the strategies that reduces nursing home admissions and ER readmissions reduces lifetime care costs, but also reduces time in the community.

Under the assumption that the implementation of composite strategies would not entail additional costs and efficiency losses associated with coordination between different health care providers, our model predicts that composite interventions that reduce nursing home admissions and additionally reduce ER and/or hospital readmissions are more cost-effective than any of the three non-composite existing interventions that we evaluated. However, this assumption might be unrealistic given the existing challenges that exist to coordinate care provision and maintain continuity of care for the dementia population. The one-way sensitivity analysis provides further insight into the consequences that efficiency losses can have on determining the cost-effectiveness of composite interventions. In pessimistic scenarios under which composite interventions would have lower effectiveness due to potential efficiency losses, composite strategies are still cost saving or cost-effective (i.e., remained on the cost-effectiveness frontier). Insensitivity to variation in treatment effects should encourage policymakers and payers to allocate resources for the implementation, evaluation, and potential reimbursement of composite interventions.

We note several limitations in our study. First, in estimating care trajectories models, we rely on dementia classification based on the information available in Medicare claims files, which has been shown to undercount dementia cases. This limitation could affect the magnitude (in absolute terms) of the estimated costs and benefits of strategies, but would not affect the assessment of the relative performance of strategies in terms of incremental benefits and costs. Second, our model does not directly incorporate the severity and progression of dementia, which limits the assignment of severity-specific costs and benefits. However, our model integrates an explicit dependence on the progression of chronic health conditions and the time since the diagnosis of dementia, both strong predictors of the progression of dementia. In future work, we will expand our model to explicitly incorporate disease progression and its influence on patterns or care over time, which will also allow the evaluation of pharmacologic interventions that slow cognitive and functional decline. Third, although we performed a one-way sensitivity analysis to evaluate scenarios assuming different strengths of treatment effects, we did not explore the potential structural sensitivity to different treatment regimes and time delays of treatment effects. This limitation could affect our assessment of benefits and costs, especially for strategies that provide long-term support, such as strategies that reduce nursing home admissions. Furthermore, we do not evaluate interventions from a societal perspective; however, previous studies evaluating the cost-effectiveness of reducing nursing home admission showed societal benefits of interventions that increase time in the community for the person with dementia (Jutkowitz et al., 2023). Since these interventions showed similar results in extending time in the community as the set of interventions that we evaluate in this study, it is likely that once evaluated, interventions that reduce ER visits and/or hospital readmissions can be cost-effective from a societal perspective. In future work, an evidence-based assessment of the societal value of these interventions will be evaluated.

Finally, even though we leveraged the richness of the data from the residential history file and other claims data to estimate care trajectories, chronic health conditions, and Medicare costs, our model still relies on different sources of evidence to inform other dynamics; for example, health-related quality of life, treatment effects, and costs associated with Medicaid reimbursed nursing home stays. The uncertainty associated with these sources of evidence will be evaluated in future work via probabilistic sensitivity analysis (forward Monte Carlo) and will provide more evidence about the robustness of our findings.

4.7 Conclusion

We identify a set of interventions and composite strategies that increase the time spent in the community by people living with dementia. The subset of these interventions with ICERS that remain below or close to the threshold of $150,000$ usd per QALY presents an opportunity to adequately serve Medicare living with dementia without incurring prohibitive expenditures. Additional gains in prolonging time in the community among people living with dementia can be achieved by implementing composite interventions that complement the benefits of reducing nursing home admissions in a cost-effective way.

4.8 Figures and Tables

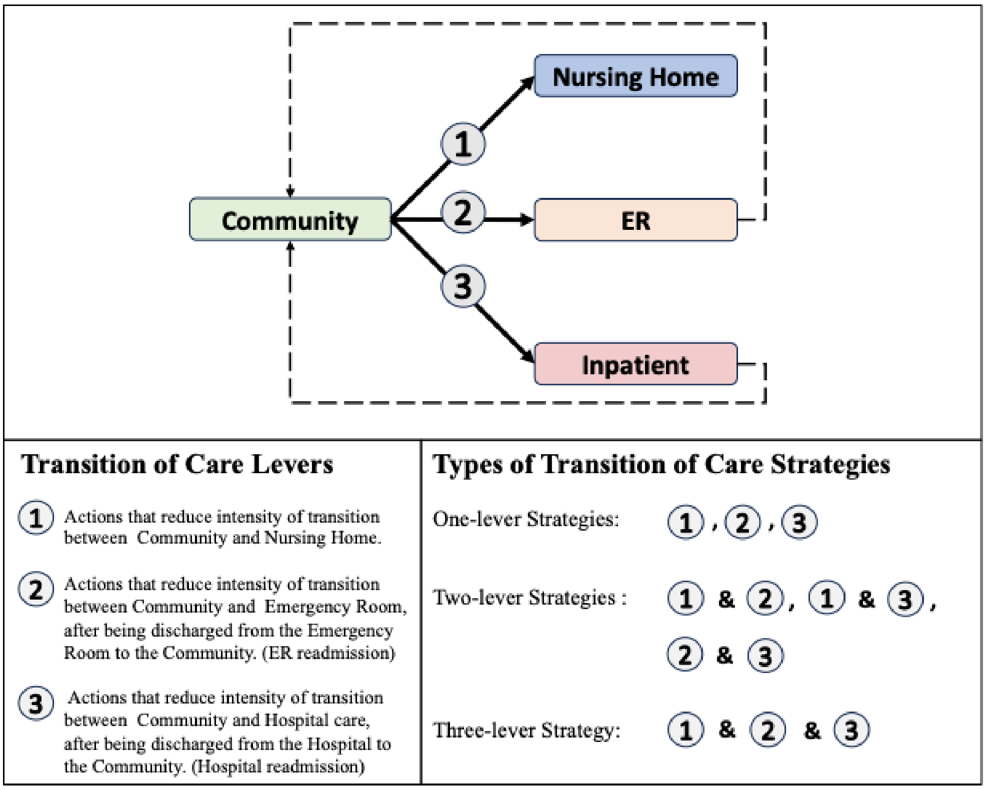


FIGURE 4.1: Transition of Care Levers and Strategies. We exclude other potential transitions that the strategies in the Figure do not influence. One-lever strategies only act on a single transition out of community-based care (levers 1, 2, or 3). Two-lever strategies act on pairs of transitions out of community-base care(pairs of levers: (1 and 2), (1 and 3), or (2 and 3)). The three-lever strategy acts on the three transition out of community-based care (levers 1 and 2 and 3).

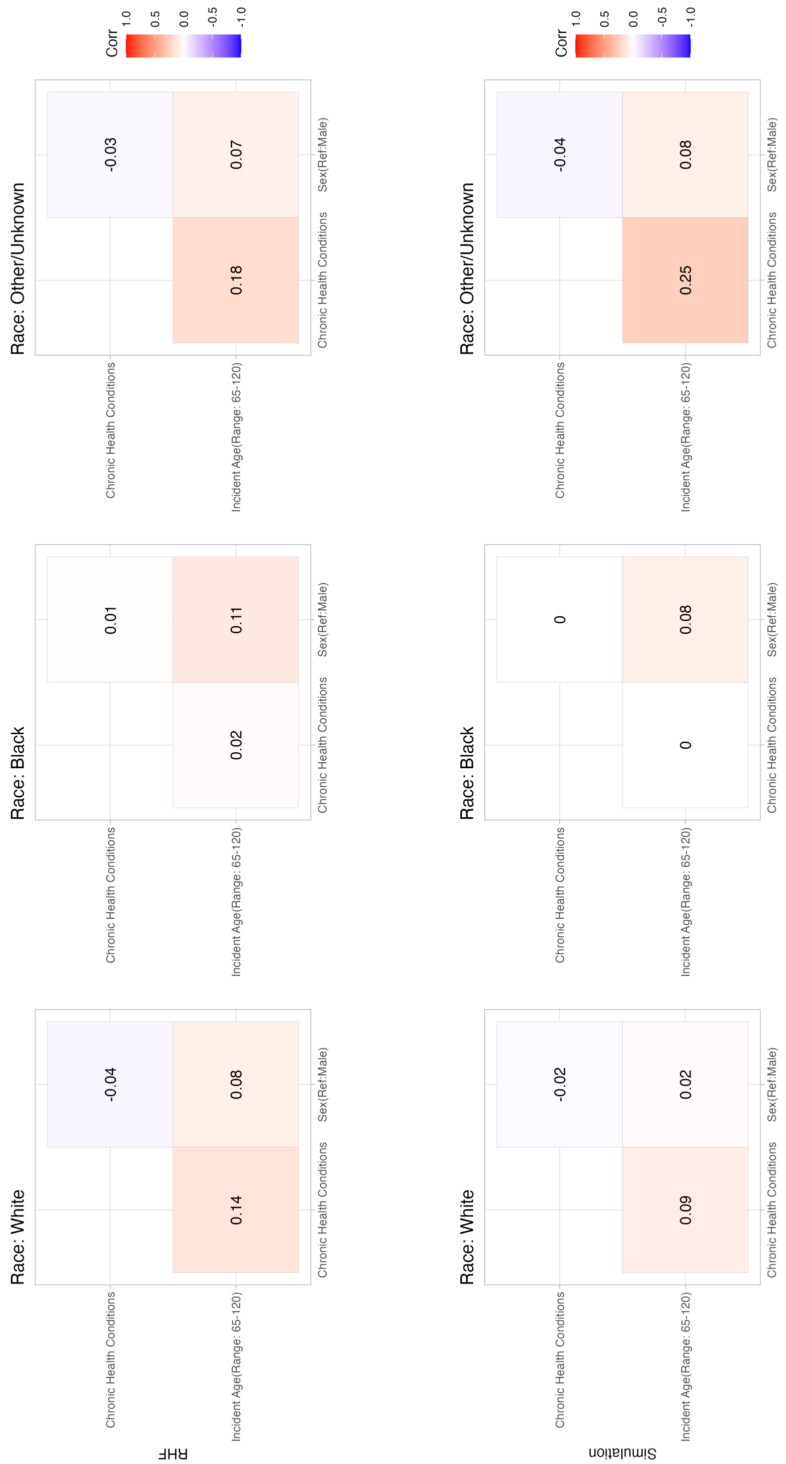


FIGURE 4.2: Correlation Matrices of Baseline Characteristics by Race, Analytic Sample versus Simulation

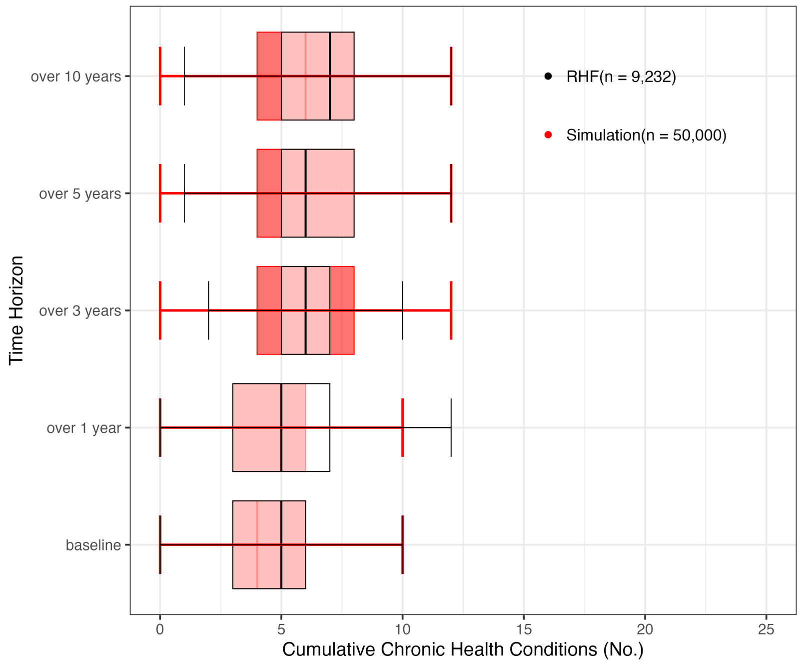


FIGURE 4.3: Interquartile Range of the Cumulative Chronic Health Conditions over different Time Horizons

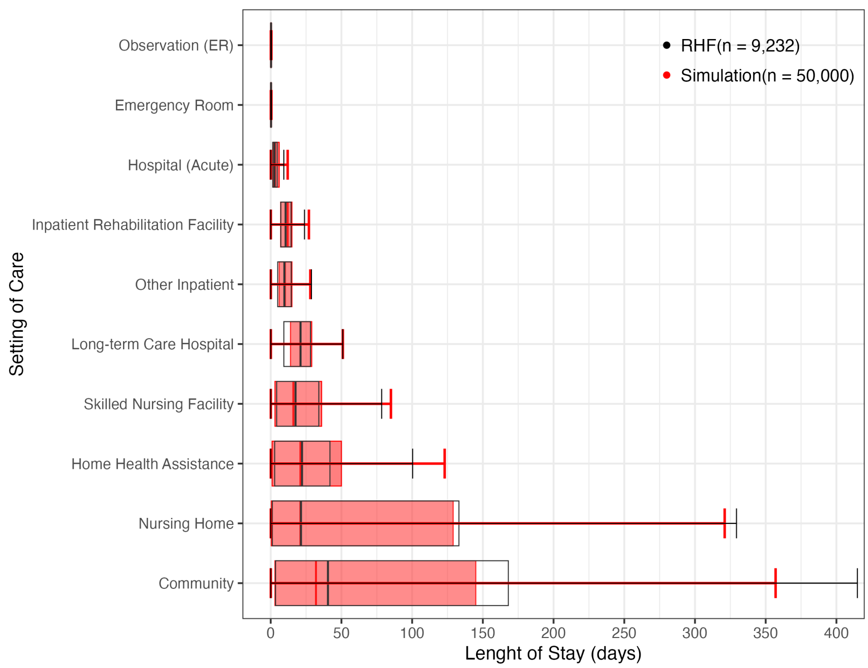


FIGURE 4.4: Interquartile Range of the Length of Stay (days) by Setting of Care

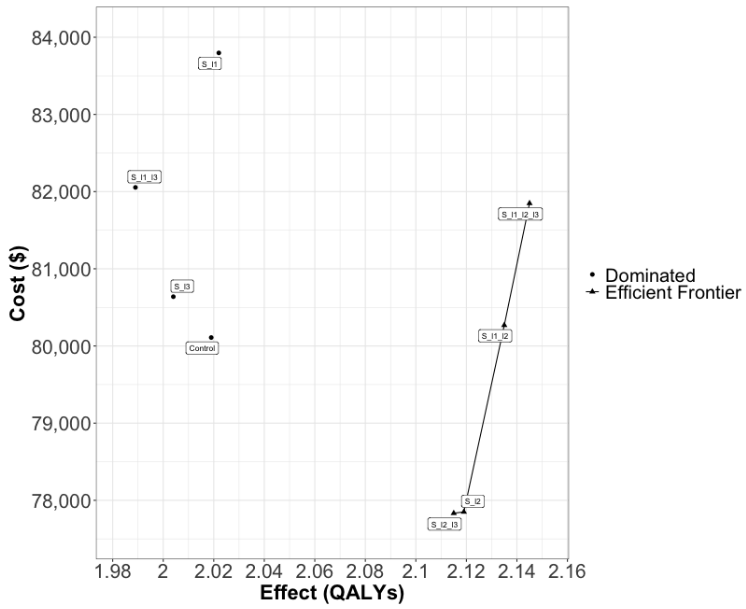


FIGURE 4.5: Cost-Effectiveness Frontier of Transitional Care Interventions that Increase Time in the Community (Effect: QALYs)

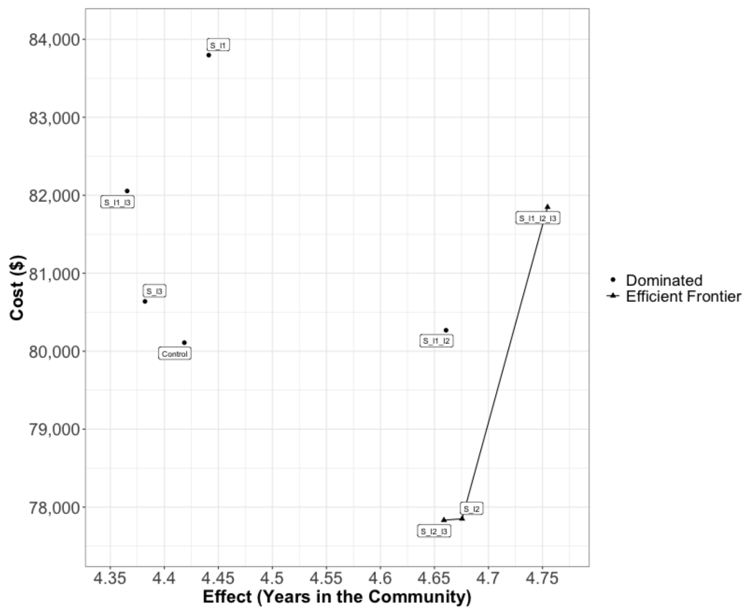


FIGURE 4.6: Cost-Effectiveness Frontier of Transitional Care Interventions that Increase Time in the Community (Effect: Years in the Community)

TABLE 4.1: Description of Intervention and Outcomes

Description of Intervention	Transition affected by intervention	Hazard Ratio (HR)	Odds Ratio (OR)	Relative Risk (RR)	Mean(sd) cost per person per month
Alzheimer's and Dementia Care (ADC): ADC offers people living with AD/ADRD and their caregivers a needs assessment, personalized care plans, and 24/7/365 access to a care manager. A nurse practitioner and physician that co-manage patients, conduct needs assessment, and develop individual care plans. Case-control design evaluation with a matched sample of 1,083 participants receiving the intervention and a comparison group of 2,166 individuals with dementia (n = 3,249).	Community-Nursing Home (C-NH)	0.65 (0.47-0.89)	not reported	not reported	$160 (20)[a]
Adapted Care Transition Intervention (adapted CTI): Modified version of the Care Transition Intervention (CTI) utilized for post-ER discharge to the community. The adapted CTI consists a single home visit within 24 to 72 hours after ER discharge, followed by one to three phone calls from a paramedic coach over the following 4 weeks. Paramedics coach participants on outpatient follow-up, self-management of medications, recognition of red-flag symptoms, and use of a personal health record. Preplanned subgroup analysis within a randomized controlled trial evaluating the effectiveness of CTI n().	30-day ER readmission after being discharged from ER to community (ER-C-ER)	not reported	0.25 (0.07,0.90)	not reported	$247 (52)[b]
Continuity of Care (CoC): Retrospective cohort study of community-dwelling dementia patients (n = 22,033), relating exposure to high and low levels of continuity of care defined as the number of different primary care providers visited for the same condition within a year.	30-day hospital readmission after being discharged from ER to community (ER-C-ER)	not reported	not reported	0.81 (0.72,0.92)	$3580.2 (105)[c]

[a] Estimate obtained from a prior evaluation of the intervention.

[b] Study reports one home visit (8hrs) and between one and three phone calls (1-4 hrs total) per patient per ER visit over 30 days after discharge to the community. FTE paramedic workers (estimated annual wage $49,400 usd) were hired to deliver the intervention; which amounts to 0.06 FTE per person per year, equivalent to $2,964 usd per person per year, or $247 usd per person per month.

[c] Estimate based on 0.075 FTE of a paramedic coach per patient per year, equating to $49,400 usd/year; equivalent to $4,297.8 usd per person per year, or $358 usd per person per month

TABLE 4.2: Baseline Characteristics

Baseline Characteristics	**Analytic Sample*** n = 9,232	**Simulation** n = 5,000	**Simulation** n = 50,000
AD/ADRD Incident Age, yrs			
65-74	2,238 (24.2%)	1,120 (21.7%)	11,055 (22.1%)
75-84	3,864 (41.9%)	2,330 (47.4%)	23,570 (47.1%)
85-94	2,852 (30.9%)	1,326 (27.0%)	13,426 (26.9%)
95	278 (3.0%)	224 (4.9%)	1,949 (3.9%)
Mean(SE)	80.5 (7.9)	80.7 (7.9)	80.7 (7.9)
Median(25th pctile., 75th pctile.)	81 (75, 87)	80 (74, 85)	81 (75, 85)
Female	5,706 (61.8%)	3,091 (61.8%)	30,850 (61.7%)
Race			
White non-Hispanic	7,790 (84.3%)	4,196 (83.9%)	42,060 (84.1%)
Black non-Hispanic	852 (9.2%)	497 (9.9%)	4,645 (9.3%)
Other/Unknown	590 (6.4%)	307 (6.1%)	3,275 (6.6%)
Baseline Chronic Health Conditions (ever diagnosed)			
Mean(SE)	4.4 (0.02)	4.3 (0.03)	4.3 (0.01)
Median(25th pctile., 75th pctile.)	4 (3, 6)	4 (3, 6)	4 (3, 6)

AD/ADRD: Alzheimer's Disease and Alzheimer's Disease Related Dementias

* Analytic sample is derived from the residential history file using 5% of all Medicare claims files for a cohort of AD/ADRD diagnosed beneficiaries between 2011 and 2020.

TABLE 4.3: Comparative Effectiveness

Scenarios*	**No. NH Admissions (C-NH),** mean(SE)	**No. 30-day ER Readmissions (ER-C-ER),** mean(SE)	**No. 30-day Hospital Readmissions (Hosp-C-Hosp),** mean(SE)	**LoS in the Community (days),** mean(SE)
18 month time horizon				
Standard of Care	0.058 (0.004)	0.284 (0.013)	0.021 (0.004)	61.226 (0.811)
Intervention 1 (C-NH)	0.037 (0.003)	0.272 (0.012)	0.017 (0.004)	61.211 (0.815)
Intervention 2 (ER-C-ER)	0.047 (0.004)	0.125 (0.01)	0.015 (0.004)	62.333 (0.854)
Intervention 3 (Hosp-C-Hosp)	0.056 (0.004)	0.289 (0.013)	0.015 (0.003)	60.895 (0.807)
Strategy (Intervention 1 & 2)	0.038 (0.003)	0.107 (0.009)	0.027 (0.005)	62.91 (0.869)
Strategy (Intervention 1 & 3)	0.037 (0.003)	0.263 (0.012)	0.016 (0.003)	61.114 (0.813)
Strategy (Intervention 2 & 3)	0.054 (0.004)	0.102 (0.009)	0.019 (0.004)	62.729 (0.86)
Strategy (Intervention 1 & 2 & 3)	0.035 (0.003)	0.105 (0.009)	0.02 (0.004)	63.33 (0.876)
lifetime time horizon				
Standard of Care	0.298 (0.015)	0.492 (0.014)	0.021 (0.003)	157.709 (1.543)
Intervention 1 (C-NH)	0.31 (0.022)	0.496 (0.019)	0.023 (0.003)	154.062 (1.49)
Intervention 2 (ER-C-ER)	0.307 (0.016)	0.396 (0.013)	0.02 (0.003)	169.968 (1.784)
Intervention 3 (Hosp-C-Hosp)	0.315 (0.019)	0.494 (0.014)	0.018 (0.002)	157.236 (1.541)
Strategy (Intervention 1 & 2)	0.262 (0.009)	0.381 (0.012)	0.025 (0.003)	173.009 (1.875)
Strategy (Intervention 1 & 3)	0.281 (0.016)	0.475 (0.014)	0.022 (0.003)	152.514 (1.493)
Strategy (Intervention 2 & 3)	0.323 (0.028)	0.377 (0.013)	0.023 (0.003)	160.914 (1.806)
Strategy (Intervention 1 & 2 & 3)	0.292 (0.013)	0.406 (0.013)	0.021 (0.003)	172.277 (1.853)

We calculate and compare the average number of NH admissions among those in the community (column 2), average number of 30-day ER readmissions among those discharged from the ER to the community (column 3), and average number of 30-day hospital readmissions among those discharged from the hospital to the community (column 4), under each strategy within each time horizon.

Average length of stay (LoS) is computed as the average duration of a community stay under each strategy within each time horizon (column 5).

C-NH, intervention that reduces transitions from community to nursing home

ER-C-ER, intervention that reduces 30-day readmissions to emergency room

Hosp-C-Hosp, intervention that reduces 30-day readmissions to hospital

LoS, length of stay Underlined values highlight the top four strategies at increasing LoS within column and time horizon in column 5.

* 50,000 simulated trajectories under each scenario

TABLE 4.4: Cost-effectiveness Analysis ($/QALY)

Scenarios*	Lifetime Cost, $	Lifetime QALYs	Incremental Lifetime Costs, $	Incremental QALYs	ICER, $ / QALY	Status
Strategy (Intervention 2 & 3)	77,832.61	2.115	NA	NA	NA	ND
Intervention 2 (ER-C-ER)	77,850.22	2.119	17.610	0.004	4,402.500	ND
Strategy (Intervention 1 & 2)	80,268.76	2.135	2,418.540	0.016	151,158.800	ND
Strategy (Intervention 1 & 2 & 3)	81,848.4	2.145	1,579.640	0.010	157,964.000	ND
Standard of Care	80,109.170	2.019	NA	NA	NA	D
Intervention 3 (Hosp-C-Hosp)	80,638.49	2.004	NA	NA	NA	D
Strategy (Intervention 1 & 3)	82,054.53	1.989	NA	NA	NA	D
Intervention 1 (C-NH)	83,797.17	2.022	NA	NA	NA	D

From a health-care payer perspective we run a competing choice, including standard of care.)
We compare:
average total lifetime costs($, column 2),
average lifetime QALYs(column 3),
average incremental lifetime costs ($, column 4),
average incremental QALYs (column 5),
incremental cost-effectiveness ratios (ICER, columns 6),
and cost-effectiveness status (dominated/not dominated, column 7) of each intervention/strategy.

C-NH, intervention that reduces transitions from community to nursing home
ER-C-ER, intervention that reduces 30-day readmissions to emergency room
Hosp-C-Hosp, intervention that reduces 30-day readmissions to hospital
LoS, length of stay
Underlined values highlight the top four strategies at increasing LoS within column and time horizon in column 5.
ICER, incremental cost-effectiveness ratio
QALY, quality-adjusted life years
D, dominated relative to standard of care
ND, not dominated
Cost Saving, positive incremental benefits and negative incremental costs relative to standard of care
* 50,000 simulated trajectories under each scenario

TABLE 4.5: Cost-effectiveness Analysis ($/Year in Community)

Scenarios*	**Lifetime Cost, $**	**Lifetime Years in Community**	**Incremental Lifetime Costs, $**	**Incremental QALYs**	**ICER, $ / Year in Community**	**Status**
Strategy (Intervention 2 & 3)	77,832.610	4.659	NA	NA	NA	ND
Intervention 2 (ER-C-ER)	77,850.220	4.676	17.610	0.017	1048.214	ND
Strategy (Intervention 1 & 2)	81,848.400	4.755	3,998.180	0.079	50552.282	ND
Strategy (Intervention 1 & 2 & 3)	80,109.170	4.419	NA	NA	NA	D
Standard of Care	80,268.760	4.661	NA	NA	NA	D
Intervention 3 (Hosp-C-Hosp)	80,638.490	4.382	NA	NA	NA	D
Strategy (Intervention 1 & 3)	82,054.530	4.366	NA	NA	NA	D
Intervention 1 (C-NH)	83,797.170	4.441	NA	NA	NA	D

From a health-care payer perspective we run a competing choice, including standard of care.)
We compare:
average total lifetime costs($, column 2),
average lifetime years in Community(column 3),
average incremental lifetime costs ($, column 4),
average incremental QALYs (column 5),
incremental cost-effectiveness ratios (ICER, columns 6),
and cost-effectiveness status (dominated/not dominated, column 7) of each intervention/strategy.

C-NH, intervention that reduces transitions from community to nursing home
ER-C-ER, intervention that reduces 30-day readmissions to emergency room
Hosp-C-Hosp, intervention that reduces 30-day readmissions to hospital
LoS, length of stay
Underlined values highlight the top four strategies at increasing LoS within column and time horizon in column 5.
ICER, incremental cost-effectiveness ratio
QALY, quality-adjusted life years
D, dominated relative to standard of care
ND, not dominated
Cost Saving, positive incremental benefits and negative incremental costs relative to standard of care
* 50,000 simulated trajectories under each scenario

Chapter 5

Conclusion and Discussion

In this dissertation, we investigate the various aspects involved in the correct quantification of collective preferences for dyads composed of people living with dementia and their informal caregivers as well as the intricate dynamics of care transitions that people living with dementia experience throughout their lifetime. We additionally assess the impact and cost-effectiveness of population-level nonpharmacoligc interventions that support people living with dementia to age safely at home.

In Chapters 1 and 2 we propose a novel model of dyadic health-related quality of life based on the Archimedean utility copula and show how to estimate this type of model from real-world data on the health status and preferences of people living with dementia and their caregivers. With this new measure, policy and decision makers can quantify and incorporate the collective gains and losses that dyads of people living with dementia and caregivers experience as a result of interventions that, for example, directly impact clinical characteristics related to dementia and indirectly impact caregiver's health status and well-being. In contrast to previous methodologies, our dyadic model of health-related quality of life takes into account the inherent interrelation that exists between the well-being of the person living with dementia and their caregivers and offers additional flexibility to model and evaluate dyadic decision problems that would typically fall outside of the scope of traditional frameworks. For example, situations where decision-makers are concerned with the health-related quality of life of the dyad but inevitably one member of the dyad will die at a different time than the other member during the time horizon of the study. This new measure is also consistent with the axioms of preference and utilities used in decision analysis and economic evaluations, allowing researchers and analysts to incorporate the collective health-related quality of life of dyads in familiar forms, such as time-trade-off weights and quality adjusted life years, thus facilitating its inclusion into standard practice.

In Chapter 3 we develop a novel discrete event system simulation to represent the dynamics of transition between settings of care among the Medicare population diagnosed with dementia. To make our model more realistic, we allow transition intensities between settings of care to vary over time. In addition, we also allow transition intensities to vary as the number of cumulative chronic health conditions of people living with dementia changes over time, as well as incorporate the effect of sociodemographic characteristics (age, sex and incident age) through stratification of transition intensity models. With this model, we obtained a reasonable representation of the patterns of transition of Medicare beneficiaries diagnosed with dementia, the average length of stay in each of these settings of care, as well as the most common transitions out of community-based care.

With this representation of the continuum of care, we evaluated nonpharmacologic transitional care interventions that reduce avoidable nursing home admissions, 30-day ER and hospital readmissions and ultimately support people living with dementia to age safely at home. In addition, we evaluate combinations of these interventions that could reduce two or three of these transitions out of community-based care. We compare interventions and composite strategies on several outcomes including the average number of nursing home admissions, 30-day ER and hospital readmissions, as well as the average length of stay in the community and the average total time in the community. Furthermore, we incorporate both lifetime care costs and QALYs to calculate incremental cost-effectiveness ratios and evaluate the cost-effectiveness of interventions and composite strategies. We found that, with the exception of the intervention that only reduces 30-day hospital readmissions and the composite strategy that reduces nursing home admissions and 30-day hospital readmissions, all strategies increase total time in the community and QALYs. Interventions and composite strategies that reduce 30-day ER readmissions are the most cost-effective since they produce the highest benefits at the lowest cost or are cost saving.

In relation to dyadic preferences and utilities, future work will extend our methodology to account for parameter and structural uncertainty, something not considered in its present formulation. In this dissertation we assumed that there was no heterogeneity in the preferences and risk aversion profiles of members of the dyads and that a single dyadic preference or utility model is a good representation of the dyadic preferences of a population of dyads. In practice, this assumption might be unrealistic, for example if a population of dyads is better represented as a mixture of different preference profiles. To address parameter uncertainty, we will integrate a Bayesian approach that allows for comprehensive quantification of uncertainty in parameter estimates, such as the uncertainty around the association parameter of the Archimedean utility copula, as well as the incorporation of prior knowledge and expert opinion on the parameters (e.g., risk aversion parameters) that describe the individual preferences of members of the dyads.

Finally, future work related to the model-based evaluation of non-pharmacological interventions will investigate the effect of parameter uncertainty in the cost-effectiveness analysis via forward Monte-carlo methodologies. Additionally, the incorporation of a module that explicitly relates dementia stage progression with patterns of transition across settings of care will allow for the evaluation and assessment of the comparative and cost-effectiveness of pharmacologic and non-pharmacologic interventions that impact clinical characteristics, such as the rate at which cognitive and functional abilities of people living with dementia decline over time. Finally, as current clinical trials evaluating new pharmacological interventions and technologies are finalized and estimates of their effectiveness are made available, we will expand our model to include a broader set of interventions and strategies and evaluate their value.

Appendix A

A.0.1 Example of a dyadic decision problem

Let us imagine two people (**Person A, Person B**) confronted with a decision that will affect them both. For simplicity, suppose that they are deciding where to go to have dinner. Person A is a cheese (C) enthusiast and Person B loves a good tomato sauce (S); naturally they narrow down their options and agree that they both want to have pizza for dinner. There are three pizza shops (PZ_1, PZ_2, PZ_3) in the neighborhood and so they most decide to which shop to go.

Can they find an option that satisfies both of them?

A.1: WEAK ORDER OVER ALTERNATIVES Both Person A and Person B must be able to establish a preference relation between the three possible pairs of pizza shops (PZ_1 vs PZ_2; PZ_2 vs PZ_3; PZ_1 vs PZ_3), i.e. they must have complete preferences; and both their preferences must be transitive, e.g. if A or B prefer PZ_1 over PZ_2, and PZ_2 over PZ_3 it must be that they prefer PZ_1 over PZ_3. We will say that they have preferences such that they can establish a weak order over the different pizza alternatives.

A.2: ATTRIBUTE AWARENESS Although Person A cares a lot about cheese and Person B cares a lot about tomato sauce, we will assume that they will consider into their decision both the quality of cheese (%fat) and the quality of sauce (simmering hours). In this scenario we will say that Person A and Person B are symmetrically aware of the two attributes of the decision alternatives, since both of them consider cheese and sauce into their preference for pizza alternatives.

"Why is this important?"

Imagine that we extract the following reviews from yelp and organize the information into the following table:

Pizza Shop	Cheese Quality (%fat)	Tomato Sauce Quality (Simmering hrs)
PZ_1	50%	2-3hrs
PZ_2	25%	4-6hrs
PZ_3	5%	1hr

Assume that for Person A more fat is better quality in cheese, and for Person B more hours simmering results in a better tomato sauce. It is easy to see that if Person A decides based only on quality of Cheese, then Person A would choose PZ_1; on the other hand, if Person B only decides based on quality of tomato sauce, then person B will choose PZ_2. In this scenario of purely individualistic awareness there is little room for agreement between Person A and Person B. However, If Person A and Person B are symmetrically aware of the two attributes of the pizza alternatives, i.e. decide based on both cheese and sauce, there is room for them to find a choice that satisfies both of them if the structure of their preferences over attributes allows it.

A.3: ADDITIVE ORDINAL PREFERENCES If Person A and B are symmetrically aware of the two attributes of pizza alternatives (cheese and sauce) there is room for them to find a common choice of pizza shop. One possibility for finding agreement in their decision relies on them having a particular way of thinking about the individual attributes of pizza alternatives, specifically that they can rank each pizza alternative based only on one of the attributes at a time. If this is the case, then their individual preferences for pizza shops can be described as the sum of their individual rankings for cheese and sauce. Each person, will then have a ranking for pizza alternatives that is the result of adding their rankings based on cheese and their rankings based on sauce. If either of them could not exert a ranking about pizza alternatives based only on one attribute at a time then we could not add the rankings of pizza alternatives to describe their preferences and would require more elaborate formulations of their preferences.

A.3: SYMMETRIC AGREEMENT Finally, for agreement to exist between Person A and Person B about the choice of pizza shops they need to have equivalent preferences over the attributes that matter to the other person. In this example we assumed that Person A preferred cheese with higher % fat but we didn't make any statements about how Person B thinks about the quality of cheese. Imagine that Person B is under a nutritional regime that constrains saturated fat consumption, so Person B actually prefers cheese with lower % fat. If this was the case, even if both Person A and Person B can establish a weak order over pizza alternatives (A.1), consider both Cheese and Sauce as decision-relevant attributes (A.2), and can rank their choices thinking about each attribute at a time (A.3), there wont be agreement in the choice of pizza alternatives, because Person B will rank lowest the alternatives that Person A ranks highest based on % fat of cheese.

Person A and Person B have to have preferences that yield equivalent orderings of pizza choices based on each attribute at a time. This means that Person B also needs to prefer more % fat for cheese and Person A must prefer tomato sauce that is simmered for longer time. For example, Person A's preferences could yield the following ranking over pizza shops based only on cheese quality $R_{A,Cheese}(PZ_1, PZ_2, PZ_3) = (3), (2), (1)$, and the following ranking based only on simmering hours of tomato sauce $R_{A,Sauce}(PZ_1, PZ_2, PZ_3) = (2), (3), (1)$. The ranking of Person A for pizza shops based on both attributes is then $R_A(PZ_1, PZ_2, PZ_3) = R_{A,Cheese} + R_{A,Sauce} = (3+2), (2+3), (1+1) = (5), (5), (2)$. Person A would be indifferent between choices PZ_1, PZ_2. Now, consider Person B' preferences (in this case completely opposite to Person A) that yield the following ranking based on cheese only $R_{B,Cheese}(PZ_1, PZ_2, PZ_3) = (1), (2), (3)$, and the ranking based on sauce only $R_{B,Sauce}(PZ_1, PZ_2, PZ_3) = (2), (1), (3)$. Person B's ranking for pizza shops based on both attributes is then $R_B(PZ_1, PZ_2, PZ_3) = R_{B,Cheese} + R_{B,Sauce} = (1+2), (2+1), (3+3) = (3), (3), (6)$. Person B would strictly prefer PZ_3. This is an example where Person A prefers more % fat in cheese and more simmering hours in tomato sauce and Person B prefers less % fat in cheese and less simmering hours in sauce. Their preferences yield different rankings based on each attribute at a time and summing these rankings yield different rankings over pizza shops.

"which preferences would yield equivalent rankings from Person A and B?"

Suppose that each Person assigns a numerical value between $(0-100)$ to each of the pizza shops based on their preference for cheese and sauce. Suppose Person A assigns $(70, 50, 10)$ to options PZ_1, PZ_2, PZ_3 based on cheese; and $(40, 60, 5)$ based on sauce. On the other hand Person B assigns $(30, 20, 10)$ based on cheese, and $(20, 30, 10)$ based on sauce. Although numerically, their preferences indicate different preferences, the rankings for both Person A and Person B are identical,i.e., for Person A and Person B the ranking based on cheese is $R_{A,cheese}(70, 50, 10) = (3, 2, 1) = R_{B,cheese}(30, 20, 10)$; and the ranking based on sauce is $R_{A,sauce}(40, 60, 5) = (2, 3, 1) = R_{B,sauce}(20, 30, 10)$.

Since for both we know we can add the individual ranking of each attribute, their preference for Pizza alternatives can be represented by the Rankings: $R_{A,Pizza} = (3+2), (2+3), (1+1) = (5), (5), (2) = R_{B,Pizza}$. In this case, since both have strictly increasing preferences over % of fat in cheese and simmering hours of tomato sauce, their preferences are represented by the same ordering ranking. In this case, both Person A and Person B would be indifferent between PZ_1 and PZ_2, and both would prefer any of these two option over PZ_3.

A.0.2 Axioms of von Neumann-Morgenstern Utility

The von Neumann-Morgenstern (vNM) utility representation relies on a set of axioms pertaining to lotteries:

- **Completeness:** asserts a complete weak order of preferences of decision alternatives. E.g.: consider decision alternatives a and b, then under completeness, I can always assert a preference relation $\succsim$ between them, such that either alternative is preferred to the other, or I am indifferent between them.

$$a \succsim b \text{ or } b \succsim a$$

- **Transitivity:** Consider three decision alternatives a, b, c. Transitivity means that if I prefer a to b ($a \succsim b$), and b to c ($b \succsim c$), then by transitivity it must be that I also prefer a to c ($a \succsim$ c).

- **Continuity:** Consider three ordered lotteries A, B, C and a complete strict order between them $A \succ B \succ C$. By continuity there exists a probability π that would make me indifferent between receiving alternative B or receiving a lottery that yields alternative A with probability π or alternative C with probability $(1 - \pi)$.

- **Independence:** Refers to the independence of preferences with respect to weighted sums of lotteries. Consider three lotteries A,B,C, if $A \succ B$ and $\alpha \in [0, 1]$, then by independence:

$$\alpha A + (1 - \alpha)C \succ \alpha B + (1 - \alpha)C$$

  and, if $A \backsim B$, then

$$\alpha A + (1 - \alpha)C \backsim \alpha B + (1 - \alpha)C$$

A.0.3 Existence and Uniqueness of a von Neumann-Morgenstern Utility Representation

In this subsection, we sketch the proof of the existence and uniqueness of a vNM numerical representation of utilities. In this subsection, I will adhere to the notation used in (Von Neumann and Morgenstern, 1947) to simplify the exposition. Reference to lemmas and theorems that appear in (Von Neumann and Morgenstern, 1947) and are used in this subsection will be bolded.

Let us first state the objective as laid out by vNM. We want a numerical representation of utilities, $w \to v(w)$, that satisfies:

- $u \succ v \implies v(u) > v(v)$, preserves weak order over consequences (**3:1:a**)
- $v\big(\alpha u + (1-\alpha)v\big) = \alpha v(u) + (1-\alpha)v(v)$, $v()$ is a linear operator (**3:1:b**)

for any u, v.

The proof of existence and uniqueness of this representation can be broken down into 3 main results, which I sketch below and with emphasis on the "uniqueness" part of the theorem.

Result 1: normalized utility function $h(w)$

Before proving that such $w \to v(w)$ exists, vNM first prove the constrained case, in which a numerical representation arbitrarily normalized to $(0,1)$, $w \to h(w)$, exists and is unique up to identity transformations. For u^*, v^* s.t. $v^* \succ u^*$, $h(w)$ has the following properties:

- $h(u^*) = 0$
- $h(v^*) = 1$
- $v \succ u \implies h(v) > h(u)$
- For $0 < \gamma < 1$ and $v \succ u$, $h\big(1-\gamma)u + \gamma v\big) = (1-\gamma)h(u) + \gamma h(v)$

Existence of $w \to v(w)$ with these properties is proven in Lemma **A:R**, and uniqueness in Lemma **A:S**. However, $w \to v(w)$ does not match the desired properties above, i.e., **3:1:a** and **3:1:b**, since $h(w)$ is normalized to an arbitrary scale and it is proven for only the case $v \succ u$.

Result 2: auxiliary Lemmas A:T and A:U

A:T states that it is always true that $(1-\gamma)u + \gamma u = u$, for $0 < \gamma < 1$, where the proof is by contradiction (not shown here). On the other hand, **A:U** states that it is always true that $h\big((1-\gamma)u + \gamma v\big) = (1-\gamma)h(u) + \gamma h(v)$, for $0 < \gamma < 1$ and for any u, v. The proof of **A:U** is illustrative since it shows that since **A:T** is true, then **A:U** holds for any u, v, i.e., $u \succ v$, $v \succ u$, or $u \sim v$.

Result 3: existence and uniqueness of $w \to v(w)$

Since the existence and uniqueness of $w \to h(w)$ is proven (not shown) as well as Lemmas **A:T, A:U**, we can now show that the mapping $w \to v(w)$ with properties **3:1:a** and **3:1:b** exists and is unique up to positive affine transformations.

Existence (A:V): Lemma **A:V** shows that with auxiliary Lemmas **A:T, A:U**, $w \to v(w)$ exists and has properties **3:1:a** and **3:1:b**. (not shown here)

Uniqueness (A:W): Uniqueness of $w \to h(w)$ is shown in three steps:

- **Result 3.1:** First, VNM show that for $v^* \succ u^*$, we can find a map, $\phi_1 : h \to v$, between a numerical representation $h(w)$ that is arbitrarily normalized to $(0, 1)$ and with properties as in **Result 1**, [1] and the numerical representation, $v(w)$, by setting

$$h(w) = \frac{v(w) - v(u^*)}{v(v^*) - v(u^*)}$$

$$\Leftrightarrow$$

$$v(w) = [v(v^*) - v(u^*)]h(w) + v(u^*)$$

$$\Leftrightarrow$$

$$v(w) = \alpha_0 h(w) + \alpha_1$$

  where $\alpha_0 = [v(v^*) - v(u^*)] > 0$, $\alpha_1 = v(u^*)$, and $v(u^*) < v(v^*)$ by definition of $v(\cdot)$

- **Result 3.2:** Similarly, we can find a map, $\phi_1 : h \to v'$, between the normalized $h(w)$ and a second numerical representation $v'(w)$, by setting

$$h(w) = \frac{v'(w) - v'(u^*)}{v'(v^*) - v'(u^*)}$$

$$\Leftrightarrow$$

[1] Lemmas **A:R, A:S** are used here.

$$v(w) = [v'(v^*) - v'(u^*)]h(w) + v'(u^*)$$

$$\Leftrightarrow$$

$$v(w) = \alpha_0' h(w) + \alpha_1'$$

where $\alpha_0' = [v'(v^*) - v'(u^*)] > 0$ and $\alpha_1' = v'(u^*)$

- **Result 3.2:** Finally, using **Results 3.1, 3.2**, vNM show that a unique mapping, $\phi : v(w) \to v'(w)$, exists between $v(w),\ v'(w)$, by equating **Result 3.1** with **Result 3.2**

$$\frac{v(w) - v(u^*)}{v(v^*) - v(u^*)} = \frac{v'(w) - v'(u^*)}{v'(v^*) - v'(u^*)}$$

$$\Leftrightarrow$$

$$\frac{v(w) - \alpha_1}{\alpha_0} = \frac{v'(w) - \alpha_1'}{\alpha_0'}$$

Then, solving for $v'(w)$ we have

$$\frac{\alpha_0'}{\alpha_0} v(w) + \frac{\alpha_0}{\alpha_0}\alpha_1' - \frac{\alpha_0'}{\alpha_0}\alpha_1 = v'(w)$$

$$\Leftrightarrow$$

$$\frac{\alpha_0'}{\alpha_0} v(w) + \frac{\alpha_0\alpha_1' - \alpha_1\alpha_0'}{\alpha_0} = v'(w)$$

$$\Leftrightarrow$$

$$w_0 v(w) + w_1 = v'(w)$$

where $w_0 = \frac{\alpha_0'}{\alpha_0} > 0$ and $w_1 = \frac{\alpha_0\alpha_1' - \alpha_1\alpha_0'}{\alpha_0}$, as desired.

It should be noted that w_0, w_1 are fixed and that any arbitrarily defined $h(w)$ can be used. Additionally, it is worth illustrating that the uniqueness theorem implies that if the two equivalent representations, $v(w),\ v'(w)$, are transformed to an arbitrary scale via ϕ_1^{-1}, and ϕ_2^{-1}, respectively, they must be identical to the normalized representation, $h(w)$. To show this, we must first verify that the inverse mappings ϕ_1^{-1}, and ϕ_2^{-1} exist. This can be easily done as follows:

For $\phi_1(h(w)) = \alpha_0 h(w) + \alpha_1$ and inverse $\phi_1^{-1}(v(w)) = \frac{1}{\alpha_0} v(w) - \frac{\alpha_1}{\alpha_0}$ we need to show that $\phi_1 \circ \phi_1^{-1} \to I_v$ and $\phi_1^{-1} \circ \phi_1 \to I_h$ hold, where $I_v,\ I_h$ are identity transformations, i.e.:

- $\phi_1\big(\phi_1^{-1}(v(w))\big) = \alpha_0[\frac{1}{\alpha_0} v(w) - \frac{\alpha_1}{\alpha_0}] + \alpha_1 = v(w)$
- $\phi_1^{-1}\big(\phi_1(h(w))\big) = \frac{1}{\alpha_0}[\alpha_0 h(w) + \alpha_1] - \frac{\alpha_1}{\alpha_0} = h(w)$, as desired

For $\phi_2(h(w)) = \alpha_0' h(w) + \alpha_1'$ and inverse $\phi_2^{-1}(v('w)) = \frac{1}{\alpha_0'} v'(w) - \frac{\alpha_1'}{\alpha_0'}$, we can show that the same conditions are met (not shown here, but easy to follow the same steps as above). Consequently, for two equivalent numerical representations $v(w),\ v'(w)$,

$$v'(w) = \phi(v(w)) \implies \phi_1^{-1}\big(\phi_1(h(w))\big) = h(w) = \phi_2^{-1}\big(\phi_2(h(w))\big)$$

where ϕ, ϕ_1, ϕ_2 are positive affine transformations, and $h(w)$ is an equivalent numerical representation with the restriction that it is normalized to an arbitrary scale. This result is trivially shown by applying ϕ_1^{-1} to **Result 3.1**, ϕ_2^{-1} to **Result 3.2** and equating the transformed results.

A.0.4 Double-cancellation Property

To verify symmetric additive ordinal preferences a simple preference assessment on both members of the dyad is required (Debreu, 1960). Consider two-attribute consequences described by levels of X, Y. If a preference relation $\succsim$ satisfies:

$$(x_1, y_1) \succsim (x_2, y_2),\ AND\ (x_2, y_3) \succsim (x_3, y_1)$$
$$\implies\ (x_1, y_3) \succsim (x_3, y_2)$$

then, $\succsim$ can be represented by an additive preference function.

A.0.5 Multi-attribute Utility Functions

For the case when $p = 1$, and a von Neumann and Morgenstern (vNM) representation of utilities over a set of acts under risk, utilities represent the probability (π) that makes a decision-maker indifferent between receiving an outcome with a specific attribute level ($Y = y$) with certainty, or receiving a binary lottery that yields the most preferred realization of Y, e.g., $max(Y)$, with probability π, and the least preferred realization of Y, e.g., $min(Y)$, with probability $(1 - \pi)$ (Abbas, 2018a).

Multi-attribute utility is an extension of vNM utility that considers models of utility under risk that involve lotteries of multiple attributes, i.e. lotteries that yield multi-dimensional consequences, $\mathbf{y} \in \mathbb{R}^p;\ p > 1$ (Keeney, Raiffa, and Meyer, 1993).

A.0.6 Two-attribute Utility Functions

In this section I summarize the main characteristics of multi-attribute utility theory (Keeney, Raiffa, and Meyer, 1993), the necessary definitions, and notation that I use in the construction of a dyadic utility function that is compatible with the Archimedean copula. In this Appendix, I only consider the bi-variate case (i.e., $p = 2$) of multi-attribute utility functions without any indexing to any of the members of the dyad, or the dyad itself.

Let Y_1, Y_2 denote two attributes of an outcome attached to acts, and let:

- $U(Y_1), U(Y_2)$denote the *marginal utility functions* over the attributes Y_1 and Y_2, respectively.
- $U(Y_1, Y_2)$ denotes the *two-attribute utility function* over Y_1 and Y_2. The two-attribute utility function represents preferences under risk over the pairs $\mathbf{Y} = (Y_1, Y_2)$. The utility obtained from $U(Y_1, Y_2)$ represents the indifference probability π that makes a decision-maker indifferent between receiving a paired outcome with specific attribute

levels $(Y_1 = y_1, Y_2 = y_2)$ with certainty, or receiving a binary lottery that yields the most preferred realization of (Y_1, Y_2), e.g., $(max(Y_1), max(Y_2))$, with probability π; and the least preferred realization of (Y_1, Y_2), e.g.,$(min(Y_1), min(Y_2))$, with probability $(1 - \pi)$.

- $U(Y_1, max(Y_2))$, $U(max(Y_1), Y_2)$ denote the *upper boundary curves of the two-attribute utility surface*. These are the curves traced on the utility surface $U(Y_1, Y_2)$, when one of the attributes is set to its maximum value. Likewise, $U(Y_1, min(Y_2))$, $U(min(Y_1), Y_2)$ denote the *lower boundary curves of the two-attribute utility surface*.
- k_{y1}, k_{y2} denote the *non-extreme corner values* ; i.e. not $(0, 0)$ or $(1, 1)$, of the two-attribute function $U(Y_1, Y_2)$. k_{y1} denotes the instantiation $U(max(Y_1), min(Y_2))$ and k_{y2} denotes the instantiation $U(min(Y_1), max(Y_2))$.
- $U(Y_1 \mid Y_2)$, $U(Y_2 \mid Y_1)$ denote the *normalized conditional utility functions*. Conditional utility functions represent utility preferences under uncertainty over one-dimensional outcomes Y_1 or Y_2, when we condition over the other attribute.

  The normalized conditional utility function of attribute Y_1 conditional on attribute Y_2 is defined as:

$$U(Y_1 \mid Y_2) = \frac{U(Y_1, Y_2) - U(min(Y_1), Y_2)}{U(max(Y_1), Y_2) - U(min(Y_1), Y_2)}$$

  We can also define the conditional utility function of one attribute conditional on a specific value of the other attribute $Y_1 = \lambda(Y_1)$ or $Y_2 = \lambda(Y_2)$. Define $\lambda(\cdot)$ as a function of the attribute that maps to a reference value in its domain, e.g., $max(\cdot)$ or $min(\cdot)$.In this case, the normalized conditional utility function, $U(Y_1 \mid \lambda(Y_2))$, represents the conditional indifference probability $\pi_{Y_2=\lambda(Y_2)}$ that makes a decision-maker indifferent between receiving the consequence $(Y_1 = y_1, Y_2 = \lambda(Y_2))$ with certainty, or receiving a binary lottery that yields the most preferred realization of Y_1 conditional on $Y_2 = \lambda(Y_2)$, e.g.: $(max(Y_1), Y_2 = \lambda(Y_2))$, with probability $\pi_{Y_2=\lambda(Y_2)}$, and the least preferred realization of Y_1 conditional on $Y_2 = \lambda(Y_2)$, e.g.: $(min(Y_1), Y_2 = \lambda(Y_2))$, with probability $(1 - \pi_{Y_2=\lambda(Y_2)})$.

$$U(Y_1 \mid \lambda(Y_2)) = \frac{U(Y_1, \lambda(Y_2)) - U(min(Y_1), \lambda(Y_2))}{U(max(Y_1), \lambda(Y_2)) - U(min(Y_1), \lambda(Y_2))}$$

A.0.7 Assumptions About the Association between Utility of Attributes

Consider two-attribute utility functions $U(Y_1, Y_2)$ that are continuous, bounded, normalized to range between 0 and 1, and are defined over the domain $[min(Y_1), max(Y_1)] \times [min(Y_2), max(Y_2)]$.

- Attribute Dominance (Abbas and Howard, 2005): For utility functions that are also strictly increasing with each attribute except at the minimum boundary values $U(Y_1, min(Y_2))$ and $U(min(Y_1), Y_2)$, the attribute dominance assumption means that if either Y_1 or Y_2 are at their minimum values, the two-attribute utility function is zero. We can express this via the 2-attribute utility function as:

$$U(min(Y_1), Y_2) = U(Y_1, min(Y_2)) = 0$$

  Under attribute dominance, the two -attribute utility function can be expressed as the product of a normalized conditional utility functions and an upper boundary utility function, as:

$$U(Y_1, Y_2) = U(max(Y_1), Y_2) * U(Y_1 \mid Y_2)$$

  This result follows from the definition of normalized conditional utility and attribute dominance condition. This assumption must not be confused with the concept of stochastic dominance between decision alternatives. See (Levy, 1992), for details on stochastic dominance.

- Mutual Utility Independence (Keeney, Raiffa, and Meyer, 1993): If one attribute Y_1 is utility-independent of another attribute Y_2, the decision-maker can declare her preferences over lotteries that involve attribute Y_1 without consideration of the level of attribute Y_2. This also means that the value of the conditional preferences over Lotteries of Y_1 conditional on a reference value of Y_2, e.g., $max(Y_2)$, does not change as we vary the reference value of Y_2. For a given realization of $Y_1 = y_1$, the conditional utilities are equivalent regardless of which reference value of Y_2 we condition on : $U(Y_1 = y_1 \mid max(Y_2))) = U(Y_1 = y_1 \mid min(Y_2))$.

  Mutual utility-independence is the special case when Y_1 is utility independent of Y_2 and Y_2 is also utility independent of Y_1 and that the decision-maker can declare her preferences over lotteries that involve attribute Y_2 without consideration of the level of attribute Y_1.

A.0.8 Utility Copula Functions

Copula functions are alternative and flexible representations of multi-attribute utility functions since they relax the attribute dominance and utility independence assumptions.

SKLAR COPULAS: Copulas where formalized in the probability and statistics literature by Sklar. The theorem that carries his name states that any continuous joint cumulative probability distribution can be expressed in terms of marginal cumulative distributions (margins) and a multivariate continuous function, C_S, known as a Sklar Copula or a Probability Copula(Nelsen, 2007). Mathematically, a Sklar Copula, C_S, is defined as a function that satisfies:

1. *Normalization*: C_S is a continuous function from $[0,1]^d$ to the closed interval $[0,1]$, such that $C_S(0,0,...,0) = 0$ and $C_S(1,1,...,1) = 1$.
2. *Marginality*: when all the arguments of C are equal to 1, but possibly for the j^{th} one, then: $C_S(1,1,...,x_j,...,1) = x_j; \ \forall j$
3. *Grounding*: $C_S(x_1,x_2,...,x_d) = 0$ if $x_j = 0$ for at least one index $j \in (1,...,d)$
4. *d-increasing*: for $d = 2$; $\forall x_1, x_2, x'_1, x'_2 \in [0,1]$; and $x_1 \leq x'_1$; $x_2 \leq x'_2$, C_S is d-increasing if the C-Volume is non-negative, i.e., $C_V = C_S(x_1,x_2) - C_S(x_1,x'_2) - C_S(x'_1,x_2) + C_S(x'_1,x'_2) \geq 0$

   (Durante and Sempi, 2016)

The properties of Sklar copulas are similar to the properties of a class of utility functions. Abbas and Howard (2005) first noted the similarity between Sklar copulas and multi-attribute utility functions, and developed the application of Sklar copulas for modelling multi-attribute utility functions under the attribute dominance condition (Abbas and Howard, 2005). They define a utility copula as follows:

UTILITY COPULAS: A utility copula $C(u_1,u_2,...,u_d)$ is a d-dimensional function that satisfies:

1. *Normalization*: C is a continuous function from $[0,1]^d$ to the closed interval $[0,1]$, such that $C(0,0,...,0) = 0$ and $C(1,1,...,1) = 1$. Note this is the same assumption as for a Skalr Copula
2. *Positive linear transformation at reference value*: when all the arguments of C are equal to 1, but possibly for the j^{th} one, then: $C(1,1,...,u_j,...,1) = \alpha_j + \beta_j * u_j; \ \forall j$ and $0 \leq \alpha_j \leq 1; \quad 0 \leq b_j \leq 1$. Note that "Marginality" in Sklar copulas corresponds to the case when $\alpha = 0; \ \beta = 1$, hence is a stronger property than for utility copulas.

3. *Attribute Dominance*: Corresponds to the "grounding" property of Sklar copulas; however the definition of a utility copulas does not require attribute dominance and it is considered as a special case.

4. *Non-decreasing*: Utility copulas may or may not comply with the $d-$increasing property of Sklar copulas. For differentiable functions, the cross-partial derivatives over the domain of the utility copula can be negative, positive , or zero. For 2 attributes X_1, X_2, for at least one fixed reference value of X_2, call it $X_2^{\lambda_2}$, the function $U(X_1, X_2^{\lambda_2})$ is strictly increasing with X_1. Class 1 utility copulas are the special case that require the $d-$increasing condition, i.e., non-negative cross partial derivatives.

From comparing both definitions we see that utility copulas are less restrictive than Sklar copulas, since only certain properties have to be met and some properties from Sklar copulas are special cases of utility copulas.

CLASS 1 UTILITY COPULAS: For the case of two attributes (i.e., $d = 2$) a *class 1 utility copula* is a function $C(s, t, k_{Y_1}, k_{Y_2})$ that represents a multi-attribute utility function that uses as arguments the conditional utility assessments of each attribute (Y_1, Y_2) when the complementary attribute is set at its upper bound, i.e., $U(Y_1 \mid max(Y_2))$, $U(Y_2 \mid max(Y_1))$; and the corner values $k_{Y_1} = U(max(Y_1), min(Y_2))$, and $k_{Y_2} = U(min(Y_1), max(Y_2))$:

$$U(Y_1, Y_2) = C(U(Y_1 \mid max(Y_2)), U(Y_2 \mid max(Y_1)), k_{y1}, k_{y2})$$

or equivalently (by the definition of conditional utility)

$$U(Y_1, Y_2) = C(U(Y_1, max(Y_2)), U(max(Y_1), Y_2))$$

The sufficient condition for a class 1 utility copula to represent a multiattribute utility function using the conditional utilities and corner values or the upper boundary utility curves is that the upper boundary curves, $U(Y_1, max(Y_2)), U(max(Y_1), Y_2)$ are continuous, bounded and strictly increasing (Abbas, 2018a). Similar constructions using the lower boundary curves (i.e., Class 0 utility copulas) are possible as well, however, we will only focus on class 1 utility copulas.

A.0.9 The Archimedean Utility Copula

Archimedean utility copulas define the class of multi-attribute utility functions over additive ordinal preferences with strictly increasing preferences over each attribute for at least one reference value of the complementary attribute(s) (Abbas and Sun, 2019a; Abbas and Sun, 2015a). Note that this preference structure coincides with the

properties of the Dyadic additive ordinal preference function under mutual agreement.
While Archimedean copulas enable both Class 1 and Class 0 copula formulations, we only focus on Class 1 Archimedean copulas, that rely on upper boundary utility assessments. This class of Archimedean utility copulas also relax attribute dominance and mutual utility independence.

A two-attribute Class 1 Archimedean copula has the form:

$$\begin{aligned} U(Y_1, Y_2) &= C\big(U(Y_1, max(Y_2)), U(max(Y_1), Y_2)\big) \\ &= \psi^{-1}\Big[\psi\big(U(Y_1, max(Y_2))\big)\psi\big(U(max(Y_1), Y_2)\big)\Big] \end{aligned}$$

where $\psi(\cdot)$ is the generating function, a nonnegative, continuous, and strictly increasing function on $[0, 1]$ such that $\psi(1) = 1$.

The main advantage of the Archimedean utility copula representation is that it takes as inputs the upper boundary curves which are uni-dimensional assessments over each individual attribute when the complementary attribute is set at its upper bound. However, there is the additional task of having to define the form of the generating function and estimate its corresponding parameter(s), a step that might involve multiple utility assessments over the domain of the two-attribute utility function. In general, the utility assessments needed for constructing a two attribute Archimedean utility copula are:

- Assessment of two complete upper boundary curves
  $U(Y_1, max(Y_2));\ U(max(Y_1), Y_2)$; and corner values k_{y1} and k_{y2}
- Assessment of one complete lower boundary curve
  $U(Y_1, min(Y_2));\ or\ U(min(Y_1), Y_2)$
- Assessment of utility values over the *"skewed diagonal path"*, which is a specific path on the domain of the two-attribute surface. The utility assessments over the *skewed diagonal path* are denoted as $S(t)$, and provide information on the trade-offs between Y_1 and Y_2 taking into account the relative distance between the corner values k_{y1}, k_{y2} and the utility dependence between attributes Y_1 and Y_2.

A potentially burdensome task involves determining the *skewed diagonal path*, i.e.,the domain of $S(t)$, since it requires to define the inverse functions of the upper boundary curves, and then directly assess $S(t)$. Additionally, once $S(t)$ has been assessed, we need to numerically estimate the generator, which requires to derive or approximate the inverse of $S(t)$ (Abbas and Sun, 2019a).

POLYNOMIAL GENERATING FUNCTION: For attribute dominance two-attribute utility functions, another alternative is to assume a specific parametric model from a large library of parametric functions that can serve as a generator function for an Archimedean Sklar copula (Abbas and Sun, 2015a) and fit data points on the surface to the parameters of the parametric generators.

However, for general Archimedean utility copulas that relax attribute dominance, it has been shown that a good approximation of the generator can be obtained through a polynomial function (Abbas and Sun, 2019a). With a sufficiently large power (m), a polynomial generator is guaranteed to match arbitrary corner values (k_{Y_1}, k_{Y_2}) of the two-attribute surface ; and provide closer approximations to the true generating function as m increases. This simplifies the assessment of the generator of any Archimedean utility copula greatly since it will not require the direct utility assessments on the *skewed diagonal path*, nor the derivation of $S(t)$ and its inverse, only m assessments on the domain of the utility surface (Abbas and Sun, 2019a).

Appendix B

B.0.1 Time tradeoff Weights and Quality Adjusted Life Years

1. Quality adjusted life years (QALYs): QALYs are outcome measures used in cost-effectiveness and cost-utility analysis. QALYs combine into a single scale: Health-related Quality of Life (HRQOL), and duration of life (survival time). QALYs are computed by multiplying each year alive times the HRQOL measure of each year. Total QALYs over a lifetime can be illustrated as the area under the curve in Figure B.1.

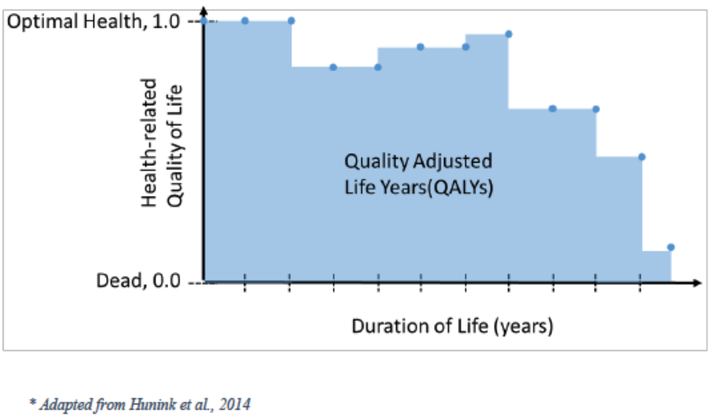


FIGURE B.1: Quality Adjusted life-Years

2. HRQOL TTO-weights: HRQOL time trade off (TTO)-weights are preference-based measure of HRQOL (Hunink et al., 2014). To obtain TTO-weights, respondents are given two choices: 1) living their remaining lifetime at their current level of HRQOL, or 2) living a fraction (x) of their remaining lifetime if they could live it in perfect health (described as a state without health problems). Respondents are asked to indicate the duration of () such that they are indifferent between the two options.

   In Figure B.2, we illustrate how the value of x is determined. To determine the ITO-weight, furst a person chooses t* such that they are indifferent between choice 1 and choice 2. Then the value of x is obtained as $x = \frac{t^*}{t}$, which represents a fraction of the expected survival years at their current HRQOL. The value they indicate for () is the corresponding TTO-weight for their current

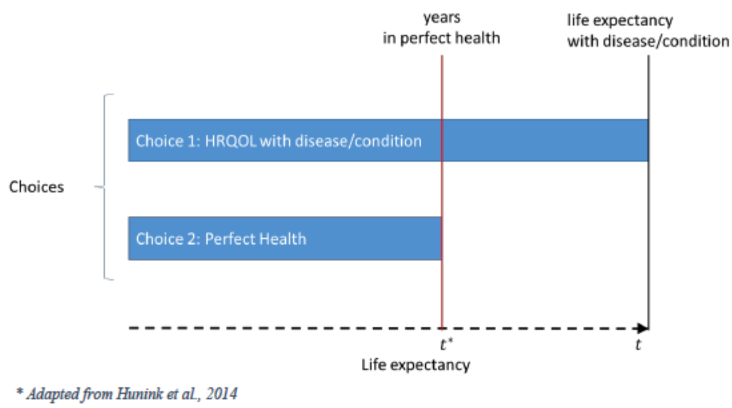


FIGURE B.2: Elicitation of TTO-weights

level of HRQOL(with disease/condition. TTO-weights are scaled to range between zero and one, where zero is interpreted as the worst HRQOL (dead), and one is interpreted as the best possible HRQOL (Lipman, Brouwer, & Attema, 2020; Lugnér & Krabbe, 2020; Torrance, 1970).

3. Dyadic TTO-Weights and Dyadic QALYs: Dyadic TTO-Weights represent the fraction (x_D) of remaining life years such that the dyad is indifferent between two choices: living their remaining life years at their HRQOL, or living that fraction (x_D) of remaining life years if they could both live it in perfect health.

   To compute dyadic QALYs the analyst should decide which survival time of the members of the dyad to use.

   - The survival time of the person living with dementia
   - The survival time of the caregivers
   - The survival time of the person who lives the longest

B.0.2 Auxiliary Tables and Figures

Functional Activity	**Coding (0 = no limitation; 1 = limitation)**
Rate her/his ability to handle small sums of money (e.g., making change, leaving a small tip, shopping)	0 = no loss 1 = some loss 1 = severe loss
Rate her/his ability to handle complicated financial or business transactions (e.g., balancing a checkbook, paying bills, doing banking, handling investments)?	0 = no loss 1 = some loss 1 = severe loss
Is s/he able to independent shop for needs	0 = usually 1 = sometimes [a] 1 = rarely [b]
Does (s/he) have more difficulty than in the past performing her/his hobbies? Hobbies may include things like sewing, painting, handicrafts, reading, entertaining, photography, gardening, going to theater or symphony, woodworking, participating in sports.	0 = no 1 = little 1 = some 1 = much
Does (s/he) have more difficulty than in the past carrying out routine household tasks, such as cooking, cleaning, laundry, taking out garbage, yard work, simple maintenance and home repair?	0 = no 1 = little 1 = some 1 = much
Does (s/he) have difficulty with feeding her/himself?	0 = no 1 = yes
Rate subject's LOSS of ability to recall recent events	0 = none 1 = some 1 = severe
Does (s/he) seem less able to understand what (s/he) reads? or Does (s/he) seem less able to understand what (s/he) sees on TV?	0 = no to both questions 1 = little loss to either question 1 = much less to either question
Compared with two years ago, how is your friend or relative at remembering things about family and friends, such as occupations, birthdays and addresses?	0 = much better 1 = a bit better 1 = not much change 1 = a bit worse 1 = much worse
Does (s/he) have more difficulty than in the past with finding his/her way around familiar streets outside the neighborhood?	0 = no 1 = yes

[a] Shops for limited number of items, buys duplicate items or forgets needed items.

[b] Needs to be accompanied on any shopping trip.

TABLE B.1: Scoring of Functional Activities of Daily Living

TABLE B.2: Average Individual TTO-weights by Self-Reported Health Status of People living with ADRD [*]

Self-reported Health Status of People living with ADRD	**TTO-weights People living with ADRD**		**Conditional TTO-weights of Caregivers [a]**	
	n (%)	**mean (sd)**	**n (%)**	**mean (sd)**
Excellent	6 (3.8%)	0.87 (0.01)	6 (3.8%)	0.85 (0.08)
Very Good	24 (15.0%)	0.83 (0.02)	24 (15.0%)	0.82 (0.10)
Good	41 (25.6%)	0.81 (0.02)	41 (25.6%)	0.86 (0.07)
Fair	44 (27.5%)	0.74 (0.02)	44 (27.5%)	0.81 (0.10)
Poor	45 (28.1%)	0.47 (0.02)	45 (28.1%)	0.80 (0.10)

n = sample size

sd = standard deviation

TTO-weights = Health-related Quality of Life Time Tradeoff Weights

ADRD = Alzheimer's Disease Related Dementias

[*] Paired Sample ($n = 160$)

[a] Conditional on People Living with ADRD's self-Reported Health

TABLE B.3: Quartiles of Individual and Combined TTO- weights by Sample

	TTO-weights People living with ADRD n=308 [a]	**n=160** [b]	**TTO-weights Caregivers n=160** [b]	**Combined TTO-weights Dyads, in-sample n=160** [c]
Mean (SD)	0.67 (0.14)	0.67 (0.14)	0.83 (0.09)	0.75 (0.05)
Min	0.43	0.44	0.51	0.62
1st Quartile	0.49	0.49	0.76	0.75
Median	0.67	0.67	0.84	0.75
3rd Quartile	0.78	0.78	0.90	0.78
Max	0.89	0.89	0.96	0.87

n = sample size

sd = standard deviation

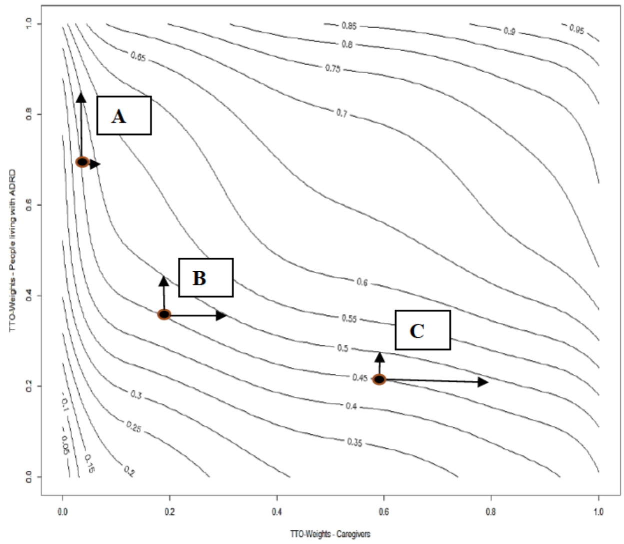
TTO-weights = Health-related Quality of Life Time Trade-off Weights

ADRD = Alzheimer's Disease Related Dementias

[c] *Paired Sample estimates using Archimedean Copula w/Quadratic Generator. In-sample estimates refer to the predicted combined TTO-weights using the observed individual TTO-weights of people living with ADRD and*

[a] *Full sample cross-walk estimates*

[b] *Paired sample cross-walk estimates*



***A, B, C** are dyads with a dyadic TTO-weight of approximately 0.45 but with different compositions/ratios of individual TTO-weights of person living with ADRD and caregiver.*
***A:** is a dyad where the caregiver has a TTO-weight <0.1 and the person living with ADRD has a TTO-weight of approximately 0.7. Interventions that prioritize increasing the caregiver's TTO-weights rather than the TTO-weights of the person with ADRD will yield a higher dyadic TTO-weight at a faster rate.*
***B**: is a dyad where the caregiver has a TTO-weight of approximately 0.2 and the person living with ADRD has a TTO-weight of approximately 0.35. Interventions that prioritize increasing the caregiver's TTO-weights will yield a higher dyadic TTO-weight at a similar rate than interventions that prioritize increasing the person living with ADRD's TTO-weights.*
***C**: is a dyad where the caregiver has a TTO-weight of approximately 0.6 and the person living with ADRD has a TTO-weight of approximately 0.25. Interventions that prioritize increasing the person living with ADRD's TTO-weights rather than the TTO-weights of the caregiver will yield a higher dyadic TTO-weight at a faster rate.*
TTO-weights = Health-related Quality of Life Time Trade-off Weights
ADRD = Alzheimer's Disease Related Dementias

FIGURE B.3: Change in Dyadic TTO-weights with different Compositions of Individual TTO-weights

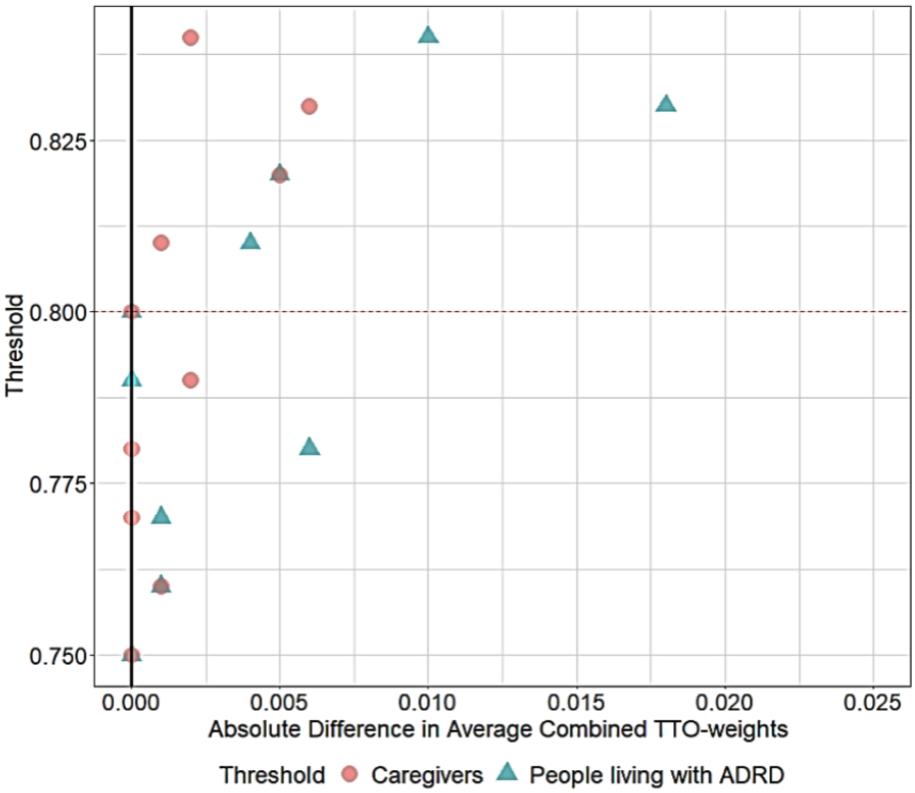


FIGURE B.4: One-way Sensitivity to Thresholds of "Highest" TTO-weights

TABLE B.4: Combined TTO-weights

TTO-weights of Person living with ADRD	TTO-weights of Caregiver																				
		0	**0.05**	**0.1**	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**	**0.5**	**0.55**	**0.6**	**0.65**	**0.7**	**0.75**	**0.8**	**0.85**	**0.9**	**0.95**	**1**
	0	0	0.141	0.187	0.203	0.218	0.236	0.255	0.273	0.288	0.299	0.307	0.313	0.320	0.330	0.343	0.359	0.375	0.390	0.403	0.418	0.446
	0.05	0.024	0.165	0.212	0.228	0.243	0.261	0.280	0.298	0.313	0.324	0.332	0.338	0.345	0.355	0.369	0.384	0.400	0.415	0.428	0.444	0.472
	0.1	0.053	0.196	0.242	0.258	0.274	0.292	0.311	0.329	0.344	0.355	0.363	0.369	0.377	0.387	0.400	0.415	0.432	0.447	0.460	0.476	0.504
	0.15	0.089	0.232	0.279	0.295	0.310	0.328	0.348	0.366	0.381	0.393	0.400	0.406	0.414	0.424	0.437	0.453	0.469	0.484	0.498	0.514	0.542
	0.2	0.128	0.272	0.319	0.336	0.351	0.369	0.389	0.407	0.423	0.434	0.441	0.448	0.455	0.466	0.479	0.495	0.511	0.526	0.540	0.556	0.584
	0.25	0.169	0.314	0.361	0.378	0.393	0.412	0.431	0.450	0.466	0.477	0.484	0.491	0.498	0.509	0.522	0.538	0.555	0.570	0.584	0.600	0.628
	0.3	0.208	0.354	0.402	0.418	0.434	0.452	0.472	0.491	0.507	0.518	0.526	0.532	0.540	0.550	0.564	0.580	0.596	0.612	0.626	0.642	0.671
	0.35	0.242	0.389	0.437	0.454	0.470	0.488	0.508	0.527	0.543	0.554	0.562	0.568	0.576	0.587	0.600	0.616	0.633	0.649	0.663	0.679	0.708
	0.4	0.270	0.418	0.466	0.483	0.499	0.517	0.537	0.556	0.572	0.584	0.591	0.598	0.606	0.616	0.630	0.646	0.663	0.679	0.693	0.709	0.738
	0.45	0.291	0.439	0.488	0.504	0.520	0.539	0.559	0.578	0.594	0.606	0.614	0.620	0.628	0.639	0.652	0.668	0.685	0.701	0.715	0.732	0.761
	0.5	0.306	0.455	0.503	0.520	0.536	0.555	0.575	0.594	0.610	0.622	0.629	0.636	0.644	0.654	0.668	0.684	0.701	0.717	0.732	0.748	0.777
	0.55	0.317	0.466	0.515	0.532	0.548	0.567	0.587	0.606	0.622	0.634	0.641	0.648	0.656	0.666	0.680	0.697	0.714	0.730	0.744	0.760	0.789
	0.6	0.328	0.477	0.526	0.543	0.559	0.577	0.598	0.617	0.633	0.645	0.652	0.659	0.667	0.678	0.691	0.708	0.725	0.741	0.755	0.771	0.801
	0.65	0.339	0.489	0.538	0.555	0.571	0.589	0.610	0.629	0.645	0.657	0.665	0.671	0.679	0.690	0.704	0.720	0.737	0.753	0.767	0.784	0.813
	0.7	0.354	0.503	0.552	0.569	0.585	0.604	0.625	0.644	0.660	0.672	0.680	0.686	0.694	0.705	0.719	0.735	0.752	0.769	0.783	0.799	0.829
	0.75	0.372	0.522	0.571	0.588	0.604	0.623	0.643	0.663	0.679	0.691	0.699	0.705	0.713	0.724	0.738	0.755	0.772	0.788	0.802	0.819	0.848
	0.8	0.394	0.544	0.594	0.611	0.627	0.646	0.667	0.686	0.702	0.714	0.722	0.729	0.737	0.748	0.762	0.778	0.795	0.812	0.826	0.843	0.872
	0.85	0.419	0.571	0.621	0.638	0.654	0.673	0.694	0.713	0.730	0.742	0.750	0.756	0.764	0.775	0.789	0.806	0.823	0.840	0.854	0.871	0.901
	0.9	0.448	0.601	0.651	0.668	0.684	0.704	0.724	0.744	0.760	0.772	0.780	0.787	0.795	0.806	0.820	0.837	0.854	0.871	0.885	0.902	0.932
	0.95	0.479	0.633	0.683	0.700	0.717	0.736	0.757	0.777	0.793	0.805	0.813	0.820	0.828	0.839	0.854	0.870	0.888	0.905	0.919	0.936	0.966
	1	0.510	0.664	0.715	0.732	0.749	0.768	0.789	0.809	0.826	0.838	0.846	0.853	0.861	0.872	0.886	0.903	0.921	0.938	0.952	0.969	1

B.0.3 Modeling framework

Attributes: We refer to factors that characterize outcomes and contribute to the preference order or ranking of the outcomes as attributes. In our analysis, the dyad considers two-attribute outcomes, each attribute represents the valuation of the health-related quality of life of each member of the dyad. However, each individual valuation considers two attributes as well, i.e., health status and remaining life time (survival time) of a member of a dyad.

Valuations: These individual valuations (i.e, numerical representation) of the health-related quality of life of members in the dyad are obtained by mapping self-reported health status and socio-demographic characteristics to health related quality of life time-trade-off weights (TTO-weights) using the cross-walk described in the main text (Nyman et al., 2007). TTO-weights are a recommended value measure for obtaining quality-adjusted life years (QALYs). The main assumption to obtain QALYs using TTO-weights is the constant proportional trade-offs between health status and remaining life-years. TTO-weights provide the value of the remaining life-time that would make a person indifferent between the deterministic outcomes of a) living a year of remaining life time in their current health state, or b) living a fraction of a year of remaining life-time in perfect health. TTO-weights are normalized to range between 0 and 1, where 0 is interpreted as the worst health-related quality of life (death), and 1 is interpreted as the best possible health related quality of life.

We denote the individual valuations of the attributes as $V_{ADRD}(X)$ and $V_{ADRD_{CG}}(X)$. These functions map factors that are associated with health-related quality of life of each member of the dyad ,X, to their respective TTO-weights. Let $\vec{v}_{ADRD} = TTOW_{ADRD}$ denote a vector of TTO-weights obtained from applying $V_{ADRD}(X)$, and $\vec{v}_{ADRD_{CG}} = TTOW_{ADRD_{CG}}$ denote a vector of TTO-weights obtained from applying $V_{ADRD_{CG}}(X)$.

The dyadic valuation of the individual TTO-weights is denoted as

$$V_{Dyad}(V_{ADRD}(X), V_{ADRD_{CG}}(X))$$

and $\vec{v}_{Dyad} = TTOW_{Dyad}$ denotes the vector of dyadic TTO-weights obtained from $V_{Dyad}()$.

Association between quality of life valuations of members of the dyads: We used the Kendall tau (τ) sample estimate to measure the association between $V_{ADRD}(X)$ and $V_{ADRD_{CG}}(X)$.

2 Attribute Archimedean Copula
Modeling assumptions:

1. The preferences of the dyad establish a weak order over the two-attribute outcomes $(TTOW_{ADRD}, TTOW_{ADRD_{CG}})$.
2. The one-person valuation functions of each member of the dyad are not individualistic,i.e. each member of the dyad considers decision relevant their own TTO-weights and the TTO-weights of their partner in the dyad.

3. Ordinal preferences of the dyad are additive and strictly increasing at least at one reference value of one of the attributes, and thus admit an Archimedean representation. This means that at a reference value of one of the attributes,e.g., when the caregiver's TTO-weights are highest, the dyad strictly prefers higher TTO-weights of the person living with dementia.
4. Boundary Valuations of each member of the dyad are identical. That is, the individual valuation function of the person living with dementia, when the caregiver's TTO-weight are highest, is identical to the valuation function of the caregiver when her own TTO weights are highest. Similarly, the valuation function of the person with dementia when her own TTO-weights are highest is identical to the valuation function of the caregiver when the TTO-weights of the person with dementia are highest.

We use a two-attribute Archimedean Copula with a quadratic generating function to combine the TTO-weights of people living with ADRD and their caregivers into a single measure. The Archimedean copula takes as argument two valuation functions, that represen the TTO-weights of each member of the dyad when the other member of the dyad's TTO-weights is at their theoretical highest value of 1 ("boundary TTO-weights") and produces a combined TTO-weight (one dimension) on a 0 to 1 scale for the dyad.

Let X^* denote the factors that define the maximum level of health related quality of life attainable by either person living with dementia or their caregiver, such that $V_{ARDR}(X^*) = TTOW^*_{ADRD} = 1$ and $V_{ARDR_{CG}}(X^*) = TTOW^*_{ADRD_{CG}} = 1$. At X^* the TTO-weights equal 1.

Now consider the one-person two-attribute valuation functions of each member of the dyad. $V_{ADRD}(TTOW_{ADRD}, TTOW_{ADRD_{CG}})$ that denotes the two-attribute valuation function from the perspective of the person living with ADRD, and $V_{ADRD_{CG}}(TTOW_{ADRD_{CG}}, TTOW_{ADRD})$ that denotes the two-attribute valuation function from the perspective of the caregiver.

The four boundary one-person two-attribute valuation functions are:

1. from the perspective of the person living with ADRD when the caregiver's TTO-weights are highest is
$$V_{ADRD}(TTOW_{ADRD}, TTOW^*_{ADRD_{CG}}),$$
2. from the perspective of the caregiver when her TTO-weights are highest is
$$V_{ADRD_{CG}}(TTOW^*_{ADRD_{CG}}, TTOW_{ADRD}),$$
3. from the perspective of the person living with ADRD when her TTO-weights are highest is
$$V_{ADRD}(TTOW^*_{ADRD}, TTOW_{ADRD_{CG}}),$$

4. from the perspective of the caregiver when the TTO-weights of the person living with ADRD are highest is

$$V_{ADRD_{CG}}(TTOW_{ADRD_{CG}}, TTOW^*_{ADRD}),$$

Finally, consider the 2 attribute valuation function from the perspective of the dyad:

$$V_{Dyad}\Big[TTOW_{ADRD}, TTOW_{ADRD_{CG}}\Big]$$

Under the Archimedean copula the dyadic valuation function requires two boundary valuation functions, that is:

1. from the perspective of the dyad and when the caregiver's TTO-weights are highest

$$V_{Dyad}\Big[TTOW_{ADRD}, TTOW^*_{ADRD_{CG}}\Big]$$

2. from the perspective of the dyad and when the TTO-weights of the person living with ADRD are highest

$$V_{Dyad}\Big[TTOW_{ADRD}, TTOW^*_{ADRD_{CG}}\Big]$$

The dyadic valuation function modeled as an Archimedean copula has the form:

$$V_{Dyad}[TTOW_{ADRD}, TTOW_{ADRD_{CG}}] =$$
$$C(V_{Dyad}[TTOW^*_{ADRD}, TTOW_{ADRD_{CG}}], V_{Dyad}[TTOW_{ADRD}, TTOW^*_{ADRD_{CG}}]) =$$
$$\psi_\alpha^{-1}\Big(\psi_\alpha(V_{Dyad}[TTOW^*_{ADRD}, TTOW_{ADRD_{CG}}]) * \psi_\alpha(V_{Dyad}[TTOW_{ADRD}, TTOW^*_{ADRD_{CG}}])\Big)$$

Where ψ_α is the quadratic generator with a single parameter α,

$$\psi_\alpha(t) = (1+\alpha)t - \alpha t^2$$

and its inverse:

$$\psi_\alpha^{-1} = \begin{cases} s & \alpha = 0 \\ \frac{\alpha+1-\sqrt{(1+\alpha)^2-4\alpha s}}{s\alpha} & \text{otherwise} \end{cases}$$

The dyadic boundary valuation functions can only be measured by eliciting the preferences and valuations of the dyads directly or indirectly by the choices made by the dyad. However, under Assumption (3) that the individual boundary valuation functions are identical between members of the dyad, we can substitute the dyadic boundary valuation functions with the boundary one-person two-attribute valuation functions and thus approximate the dyadic boundary valuation functions using individual boundary valuation functions that can be obtained from paired data. After substitution, we obtain:

$$V_{Dyad}[TTOW_{ADRD}, TTOW_{ADRD_{CG}}] =$$
$$\psi_\alpha^{-1}\Big(\psi_\alpha(V_{ADRD_{CG}}[TTOW^*_{ADRD}, TTOW_{ADRD_{CG}}]) * \psi_\alpha(V_{ADRD}[TTOW_{ADRD}, TTOW^*_{ADRD_{CG}}])\Big)$$

Finally, the parameter α of the quadratic generator is approximated with the sample estimate of Kendall's τ, an empirical measure of concordance between $V_{ADRD_{CG}}\left[TTOW^*_{ADRD}, TTOW_{ADRD_{CG}}\right]$ and $V_{ADRD}\left[TTOW_{ADRD}, TTOW^*_{ADRD_{CG}}\right]$.

Appendix C

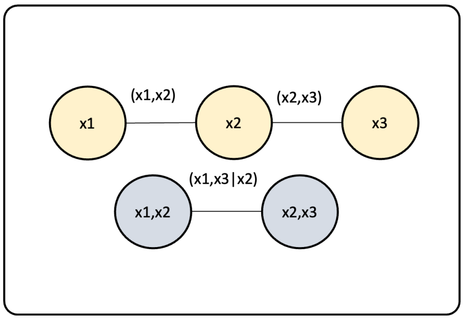


FIGURE C.1: 3-Dimensional Vine Copula Diagram of Joint Distribution of Baseline Characteristics within Race Strata

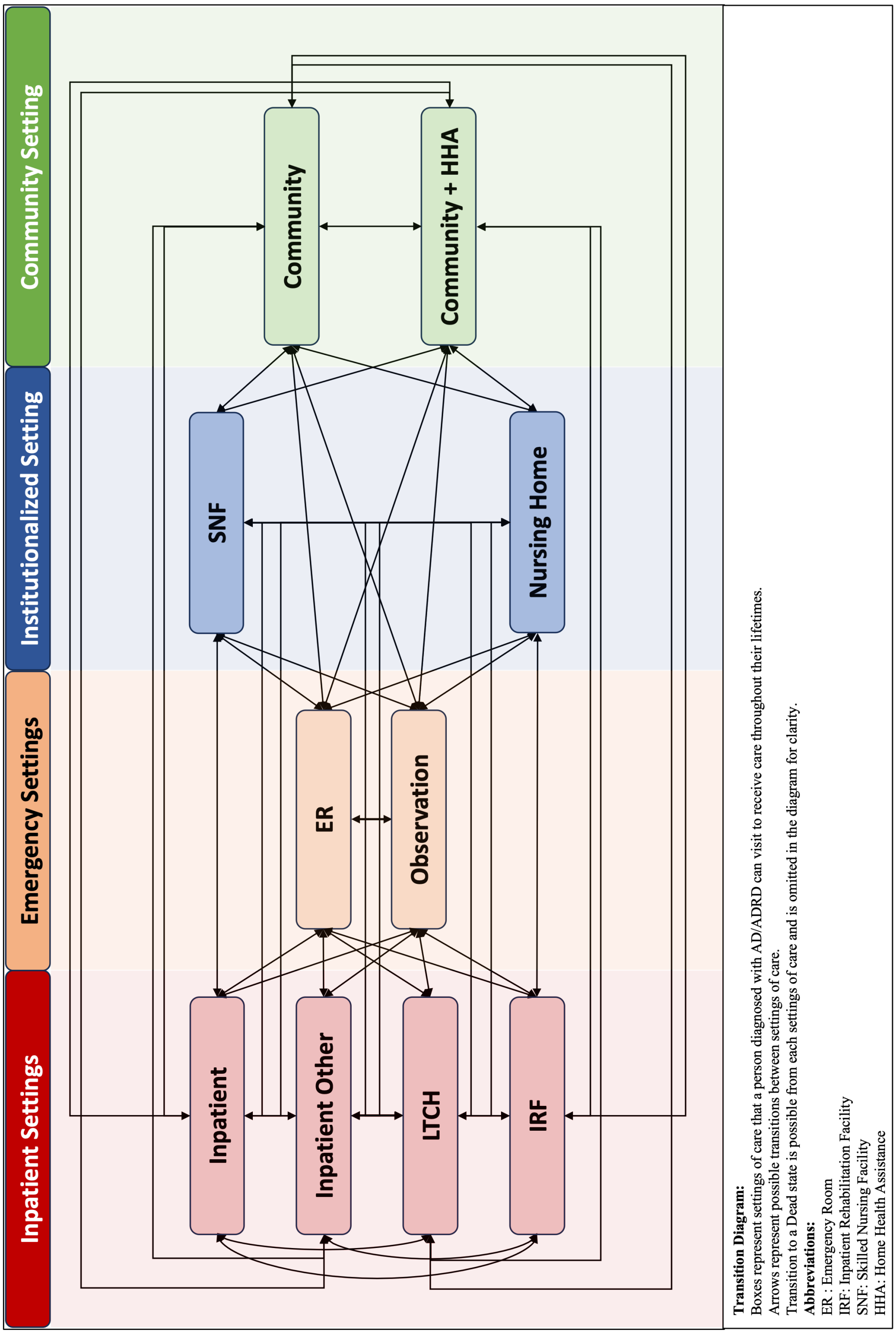


FIGURE C.2: Transition Diagram of DES simulation

TABLE C.1: Simulation Parameters

Parameters/ Models	Description	Stratified	Data Sources/References
Baseline Characteristics	The joint distribution of four baseline characteristics was fitted in two steps following the factorization $f(X_1, X_2, X_3, X_4) = f(X_1) * f(X_2, X_3, X_4 \| X_1)$: First, a distribution of race categories was fitted to data. Second, within each race category, conditional joint distributions of the three characteristics (incident-age, sex, and cumulative number of chronic health conditions) were fitted using three-dimensional Vine Copulas.	NA	RHF- Analytic Sample*
Rates of transitions between Settings of Care and Dead	A system of transition-specific intensity functions (hazards) was fitted to data using a multi-state model that allowed for parametric (Weibull, exponential, gamma, or log-normal) and flexible parametric specifications (2, 3, or 5 internal knots, in the odds or hazard scale) as well as different covariate adjustments of the intensity functions that describe rates of transitions between pairs of settings of care and dead.	yes	RHF- Analytic Sample
Rates of Chronic Health Conditions	We model the count of incident cases of chronic health conditions during the time interval between settings of care. For each possible transition, count models can follow any of three distributional assumptions of the counts: a) Poisson, b) negative binomial (modeling over-dispersion), and c) hurdle model (modeling excess zeros). Models are adjusted to four potential covariates: a) setting of care currently in, b) number of chronic health conditions at baseline, c) number of chronic health conditions at exit of the previous setting of care, and d) age of exit of the current stay.	yes	RHF- Analytic Sample
Costs	a. etting-specific costs of Care (Medicare): We consider Medicare reimbursed cost for skilled nursing facility stays, hospital stays, and other inpatient stays (e.g., Long-term care Hospital, Inpatient Rehabilitation Facility, Inpatient Psychiatric Facility), ER visits that lead to an inpatient stay, ER visits that do not lead to an inpatient stay, and home-health assistance visits. We fit longitudinal generalized gamma regressions (with logistic link function) to account for non-negative and skewed data. We adjust for incident age, sex, race, and cumulative chronic health conditions, time trends may follow linear, quadratic, or cubic specifications.	no	RHF- Analytic Sample and Cost and use segment of MBSF **
	b. Probability of Medicaid-reimbursed nursing home stay: Longitudinal binary logistic regression model to model the probability of Medicare beneficiaries to be dually eligible to Medicaid and experience a nursing home stay as a function of incident age, sex, race, cumulative chronic health conditions and time. We use a restricted cubic spline of logarithmic transformed time.	no	RHF- Analytic Sample
	c. Nursing home cost (Medicaid): beneficiaries who are projected to be dually eligible and experience a nursing home stay are assigned a cost per day as reported in the literature.	no	Bharmal et al. (2012) & Kaiser Family Foundation (2024)
	d. Observation stay at ER (Medicare): beneficiaries who experience episodes in the ER we assign costs for Medicare based on what is reported in the literature.	no	Burke et al. (2020)
	e. Intervention costs: The intervention that affects transition rates from the community to nursing homes, ADC, costs $106.00 usd per month as reported in the literature. For the intervention that reduces 30-day emergency department and hospital readmissions, the costs per person per month are not reported. For these interventions, we used study data on the type and number of personnel needed to deliver each intervention to impute the cost per person per day. For the modified CTI intervention that reduces 30-day ER readmissions we calculate that the cost per person per month is $247.00 usd, and for the hypothetical intervention that reduces 30-day hospital readmissions we estimate a cost per month of $358.15 usd. For composite strategies, we assume that the costs of each of the one-low interventions are summed.	no	Jennings et al., 2019 (ADC) & Shah et al., 2022 (CTI)& Godard-Sebillotte et al., 2021 (Continuity of Care)

* RHF-Analytic Sample: 5% random sample of all claims files between 2011-2020 and nursing home Minimum Data Set (MDS), Intrator et al., (2011)

** Cost and Use segment of the MBSF: 5% random sample of the master beneficiary summary file of CMS linked to the RHF-Analytic Sample that includes costs for different types of health services reimbursed by Medicare.

TABLE C.2: Chronic Health Conditions Burden/Dementia Stage

Setting of Care	Exponential decline rate of HRQOL	Low Burden / Mild Dementia Stage (Baseline)	Medium Burden/ Moderate Dementia Stage	High Burden/ Advance Dementia Stage
Nursing Home	normal decline	0.71[a]	0.43	0.31
Skilled Nursing Facility	normal decline	0.70	0.42	0.30
Community	slow decline	0.68[a]	0.47	0.37
Community + HHA*	slow decline	0.67	0.47	0.37
Inpatient (LTCH)**	normal decline	0.66	0.43	0.29
Inpatient (Acute)	fast decline	0.65	0.36	0.25
Other Inpatient***	fast decline	0.65	0.36	0.25
ER	fast decline	0.50	0.28	0.19
Observation (ER)	fast decline	0.50	0.28	0.19

Preference weights for people living with dementia are modeled as a function of the cumulative number of chronic health conditions and setting of care they are currently at.
Baseline preference weights are assumed to correspond to low burden of chronic health conditions (0.3), and are scaled by an exponential factor that depends on the number of chronic health conditions and the setting of care.
The scaling factor may decline at three different rates depending on the setting of care, slow decline is considered for community settings since these are settings where typically people living with dementia spend the most amount of time; normal decline is considered for Nursing Home, Skilled Nursing Facilities and Long-term Care Hospitals; finally fast decline rates are considered for Inpatient and Emergency settings.

* Home Health Assistance

** Long-term Care Hospital

*** Other Inpatient Settings that include Inpatient Rehabilitation Facilities and Inpatient Psychiatric Facilities

a values extracted directly from Jutkowitz et al. (2023)

Algorithm 1 Discrete Event System (DES) Simulation: Initial configuration considers a population of community-dwelling people diagnosed with dementia. Initial time T_0 is anchored to the time at which diagnosis was adjudicated and set to zero.

Require: $R(t)$: Cumulative intensity matrix, $|S|$ x $|S|$, with elements $r_{r,s} = \Lambda_{r,s}(t)$
Require: $R^*(t)$: Inverse cumulative intensity matrix, $|S|$ x $|S|$, with elements $r^*_{r,s} = \Lambda^-_{r,s}(u)$
Require: A: Adjacency matrix, $|S|$ x $|S|$, with elements $a_{r,s} = \{1 \ \ if \ \ r \rightarrow s; \ 0 \ \ else\}$
Require: h: Time horizon, scalar
Require: n_0: Initial population size, scalar

First Transition:
Initialize time, $T_0 \leftarrow 0$ ▷ Vector of length n
Initialize setting of care, $X(T_0) \leftarrow$ "Community" ▷ Vector of length n
for each $i \in 1{:}n_0$ **do**
    $s' := which(A_{Community,j} == 1)$ ▷ Set of possible transitions
    for each $j \in s'$ **do**
        $\tau_{Community,j} \leftarrow \tau_{Community,j} \sim F(\tau)_{Community,j}$ ▷ Algorithm 5 from 'nhpp'
    end for
end for
for each $i \in 1 : n_0$ **do**
    $\tau^*_{Community,\mu} \leftarrow min(\tau_{Community,1}, \tau_{Community,2}, \dots \tau_{Community,|s'|})$
    $T_n \leftarrow T_0 + \tau^*_{Community,\mu}$ ▷ Updated time
    $X(T_n) \leftarrow \mu$ ▷ Updated setting of care
    if $X(T_n) ==$ "Dead" **then**
        drop $X(T_n)$ ▷ Exclude those who die
    end if
end for
$n \leftarrow$ length$[X(T_n)]$ ▷ Updated population size
return $(X(T_n), T_n)$

After first Transition:
while $n > 0$ **do** ▷ Stopping Criteria
    for each $i \in 1 : n$ **do**
        $s' := which(A_{X(T_n),j} == 1)$ ▷ Set of possible transitions
        for each $j \in s'$ **do**
            $\tau_{X(T_n),j} \leftarrow \tau_{X(T_n),j} \sim F(\tau)_{X(T_n),j}$ ▷ Algorithm 5 from 'nhpp'
        end for
    end for
    for each $i \in 1 : n$ **do**
        $\tau^*_{X(T_n),\mu} \leftarrow min(\tau_{X(T_n),1}, \tau_{X(T_n),2}, \dots \tau_{X(T_n),|s'|})$
        $T_n \leftarrow T_n + \tau^*_{X(T_n),\mu}$ ▷ Updated time
        $X(T_n) \leftarrow \mu$ ▷ Updated setting of care
        if $X(T_n) == ''Dead''$ **then**
            drop $X(T_n)$ ▷ Exclude those who die
        end if
    end for
    $n \leftarrow$ length$[X(T_n)]$ ▷ Updated population size
    return $(X(T_n), T_n)$
end while

Note: Simplified version not considering time-varying covariates nor stratification. $R(t)$, $R^*(t)$, and h are required for Algorithm 5 from 'nhpp'(Trikalinos and Sereda, 2024). The index ($_n$) in T_n is used for denoting the n^{th} event time and not related to the population size. S denotes the set of possible settings of care that a person in the simulation can transit to.

TABLE C.3: Cost-effectiveness vs Standard of Care

Scenarios*	**Incremental Total Years (days) in the Community**	**Incremental QALYs**	**Incremental Lifetime Costs, $**	**ICER, $ / Year in the Community**	**ICER, $ / QALY**
Standard of Care	reference	reference	reference	reference	reference
Intervention 1 (C-NH)	0.02 (8.24)	0.1	3,688.00	163,330.38	1,229,333.33
Intervention 2 (ER-C-ER)	0.26 (9.82)	0.1	-2,258.95	Cost Saving	Cost Saving
Intervention 3 (Hosp-C-Hosp)	-0.04 (-13.3)	-0.015	529.32	D	D
Strategy (Intervention 1 & 2)	0.24 (88.4)	0.116	159.59	658.95	1,375.78
Strategy (Intervention 1 & 3)	-0.05 (-19.32)	-0.03	1,945.36	D	D
Strategy (Intervention 2 & 3)	0.24 (87.68)	0.096	-2,276.56	Cost Saving	Cost Saving
Strategy (Intervention 1 & 2 & 3)	0.34 (122.68)	0.126	1,739.23	5,174.43	13,803.41

From a health-care payer perspective we calculate and compare:
average incremental total years in the community (years/days, column 2),
average incremental quality-adjusted life-years (QALYs, column 3),
average incremental lifetime costs ($, column 4),
and incremental cost-effectiveness ratios (ICER, columns 5 and 7) under each intervention/strategy compared to standard of care.

C-NH, intervention that reduces transitions from community to nursing home
ER-C-ER, intervention that reduces 30-day readmissions to emergency room
Hosp-C-Hosp, intervention that reduces 30-day readmissions to hospital
LoS, length of stay
Underlined values highlight the top four strategies at increasing LoS within column and time horizon in column 5.
ICER, incremental cost-effectiveness ratio
QALY, quality-adjusted life years
D, dominated relative to standard of care
Cost Saving, positive incremental benefits and negative incremental costs relative to standard of care
* 50,000 simulated trajectories under each scenario

TABLE C.4: One-way Sensitivity Analysis

Intervention/Strategy	Scenario of Treatment Effect*			Health-care Payer Perspective	
	Lever 1 (C-NH)	**Lever 2 (ER-C-ER)**	**Lever 3 (Hosp - C - Hosp)**	**ICER, $ / Year in the Community**	**ICER, $ / QALY**
Intervention (lever 1 only)	pessimistic	-	-	290,122.67	1,934,151.11
	optimistic	-	-	120,966.40	806,442.67
Intervention (lever 2 only)	-	pessimistic	-	Cost Saving	Cost Saving
	-	optimistic	-	Cost Saving	Cost Saving
Intervention (lever 3 only)	-	-	pessimistic	D	D
	-	-	optimistic	D	D
Strategy (lever 1 & 2 only)	pessimistic	pessimistic	-	11,902.39	32,356.00
	pessimistic	optimistic	-	4,959.64	13,251.70
	optimistic	pessimistic	-	5,326.46	14,880.27
	optimistic	optimistic	-	1,024.57	2,785.23
Strategy (lever 1 & 3 only)	pessimistic	-	pessimistic	D	D
	pessimistic	-	optimistic	D	D
	optimistic	-	pessimistic	D	D
	optimistic	-	optimistic	D	D
Strategy (lever 2 & 3 only)	-	pessimistic	pessimistic	Cost Saving	Cost Saving
	-	pessimistic	optimistic	Cost Saving	Cost Saving
	-	optimistic	pessimistic	Cost Saving	Cost Saving
	-	optimistic	optimistic	Cost Saving	Cost Saving
Strategy (lever 1 & 2 & 3)	pessimistic	pessimistic	pessimistic	19,525.62	53,403.39
	pessimistic	pessimistic	optimistic	16,297.46	44,447.63
	pessimistic	optimistic	pessimistic	7,968.54	21,298.40
	pessimistic	optimistic	optimistic	6,839.75	18,278.63
	optimistic	pessimistic	pessimistic	10,567.17	29,940.31
	optimistic	pessimistic	optimistic	8,451.91	23,790.57
	optimistic	optimistic	pessimistic	3,277.32	8,938.15
	optimistic	optimistic	optimistic	2,477.00	6,745.88

Pessimistic/optimistic treatment effects are defined as hazard ratios reported in the literature scaled by a factor $(1-k)$ for pessimistic scenarios or $(1+k)$ for optimistic scenarios, where $k = 0.25$.
C-NH, intervention that reduces transitions from community to nursing home
ER-C-ER, intervention that reduces 30-day readmissions to emergency room
Hosp-C-Hosp, intervention that reduces 30-day readmissions to hospital
ICER, incremental cost-effectiveness ratio
QALY, quality-adjusted life years
D, dominated relative to standard of care
Cost Saving, positive incremental benefits and negative incremental costs relative to standard of care
* We run 1,000 trajectories for each strategy under each scenario.

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