ADAPTIVE PAIN MANAGEMENT DECISION SUPPORT SYSTEM

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ABSTRACT

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Pain management is an international health issue. The Eugene McDermott Center for Pain Management at the University of Texas Southwestern MedicalCenter at Dallas conducts a two-stage interdisciplinary pain management program that considers a wide variety of treatments. Prior to treatment (stage 1), an evaluation records the patient's pain characteristics, medical history and related health parameters. A treatment regime is then determined. At the midpoint of their program (stage 2), an evaluation is conducted to determine if an adjustment in the treatment should be made. A final evaluation is conducted at the end of the program to assess final outcomes.

The structure of this decision-making process uses dynamic programming (DP) to generate adaptive treatment strategies for this two-stage program. Our stochastic DP formulation considers the expected final outcomes when determining treatment. An approximate DP solution method is employed in which state transition models are constructed empirically based on data from the pain management program, and the future value function is approximated

using state space discretization based on a Latin hypercube. The state transition probabilistically models how a patient's pain characteristics change from stage 1 to stage 2. The optimization seeks to minimize pain while penalizing excessive.

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CHAPTER 1

INTRODUCTION

1.1 Background

Pain management is an international health issue. The World Health Organization (WHO) estimates that 20% of individuals worldwide have some form of chronic pain (Schatman & Champbell 2007). In the United States, chronic pain has become a major health care problem. The cost of chronic pain has been incrementally growing and is estimated at billions of dollars annually (D'Arcy et al. 2007). Before the past decade, all pain was assumed to be the same, and analgesic medications were the only treatment option. However, more and more evidence shows that standard medical treatments cannot cure or reduce patients' pain. The idea of multi-disciplinary and interdisciplinary pain management was proposed and is being developed widely (Schatman & Champbell 2007, Spanswick & Main 2000, Gould 2007). With more treatment options and new medications, one question arises: how can physicians determine the best treatment plan? These judgments can be subjective and depend on patients' information and physicians' experiences (Scheafer et al. 2004). An adaptive treatment strategy is a set of decision rules that state how treatment level and type should be adjusted depending on patients' responses (Murphy's 2003). This is a relatively new research, and adaptive treatment strategies have been studied for a number of areas (Collins et al. 2007, Murphy et al. 2007, Pineau et al. 2007), but not for pain management. In this dissertation, a framework for adaptive pain management is proposed to identify decisions that control a patient's current and future pain outcomes.

In the pain management, depending on the treatments that have been applied, patients will experience different pain outcomes at the time of diagnosis versus following treatment. The objective of pain management is to control and reduce pain and its effects. The goal of adaptive

pain management is to use patients' past and current information to identify the best treatment for controlling current and future pain outcomes. Because pain is a chronic condition, the patient and physician need to set a target to be achieved by a specified time via a pain management program. The patient's pain characteristics and related health parameters would be monitored and reviewed during the program. At each review, the physician can alter the choice of treatment based on the patient's latest pain and health readings (Robbins et al. 2003).

Patients experience different pain outcomes depending on many factors. To enable a more adaptive treatment of pain, a multi-stage program that considers a variety of treatment options was developed at the Eugene McDermott Center for Pain Management at the University of Texas Southwestern Medical Center at Dallas. In this program, patients' pain characteristics, related health parameters and pain levels are monitored and reviewed at four evaluation points – pre, mid, post, and one-year following. The data employed here was collected from August 1998 to May 2001, involving 127 patients (Robbins et al. 2003). In particular, the Center achieves interdisciplinary pain treatment via a two-stage program, as shown in Figure 1.1.

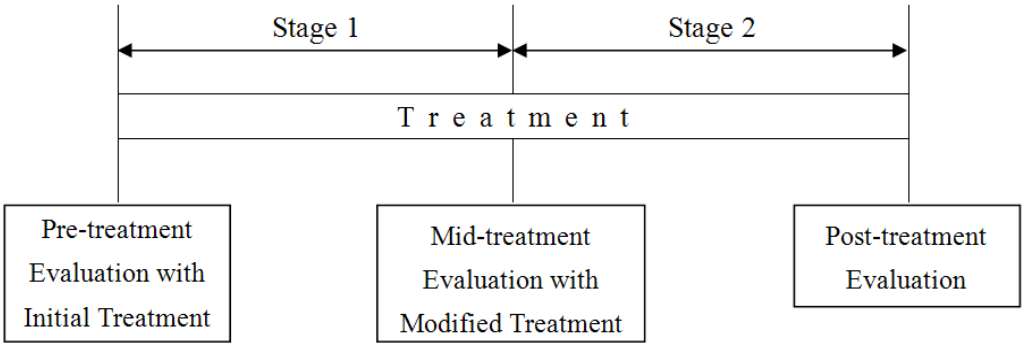


Figure 1.1: Two-stage interdisciplinary pain management program.

Stage 1 begins when a pre-treatment evaluation is conducted on the patient. The evaluation was based on their background and characteristics including their detailed review of the medical records and physical examination. The Center physicians then customize a pain

treatment plan for the patient and the treatment plan is applied. Stage 2 begins when a mid-treatment evaluation is conducted to establish how the patient is responding to the treatment plan. The period of time between stages varied for different patients. Some periods were 6-months; some only were 1-month. Depending on their results on the mid-treatment evaluation, the treatment plan could be modified at this point. Upon completing Stage 2, a post-treatment evaluation is conducted. Pain management recommendations are given to the patient and an additional evaluation is conducted one year after completion of the program. This last evaluation is not considered in the current framework because, officially, patients have completed the program upon post-evaluation.

1.2 Research Methodology Overview

This dissertation develops adaptive pain management using a decision support system (DSS) based on stochastic dynamic programming (DP). It is referred to as the adaptive pain management DSS. The goal of our adaptive pain management DSS is to minimize treatment cost and outcome measures of pain by using the patient's past and present information. We are limited here by the information collected within the Robbins et al. (2003) database. Specifically, our DSS uses a two-stage dynamic programming (DP) framework. DP is an optimization approach for multi-stage problems and has been applied for solving problems in a variety of systems such as manufacturing systems, finance, environmental engineering and others (White 1985, 1988, Scheafer et al. 2004 and Yang 2004). Figure 1.2 illustrates the basic DSS framework.

In the DSS, the first task is to specify the state and decision variables and stages. State variables in this case include the patients' relevant medical background, such as age, gender, surgical and physical histories, and past diagnoses. Decision variables consist of 42 types of treatment options (21 pharmaceutical treatments and 21 procedural treatments). Stage 1 state variables are taken from the pre-evaluation. Stage 2 state variables are taken from the pre- and mid-evaluations and from the first treatment plan.

The second task is to identify the cost objectives and constraints. Our primary cost is represented by the outcome measures for pain, which we desire to minimize. However, for some patients an acceptable or "normal" outcome measure is sufficient, and we want to avoid unnecessary treatment. Hence, our cost objective will consist of an increasing utility cost function for treatment and a penalty cost function for pain outcomes. Three outcome measures of pain levels are monitored: Beck Depression Inventory (BDI), which is a self-reported measure of depression (depression is commonly associated with pain); Oswestry Pain Disability Questionnaire (OSW), which is a measure of perceived functional disabilities caused by pain; and Pain Drawing Analogue (PDA), which is a measurement in which patients mark their level of pain along a 10-cm visual analog scale. The constraints in this research are the limitations on dosage of medication and treatment options (Robbins et al. 2003).

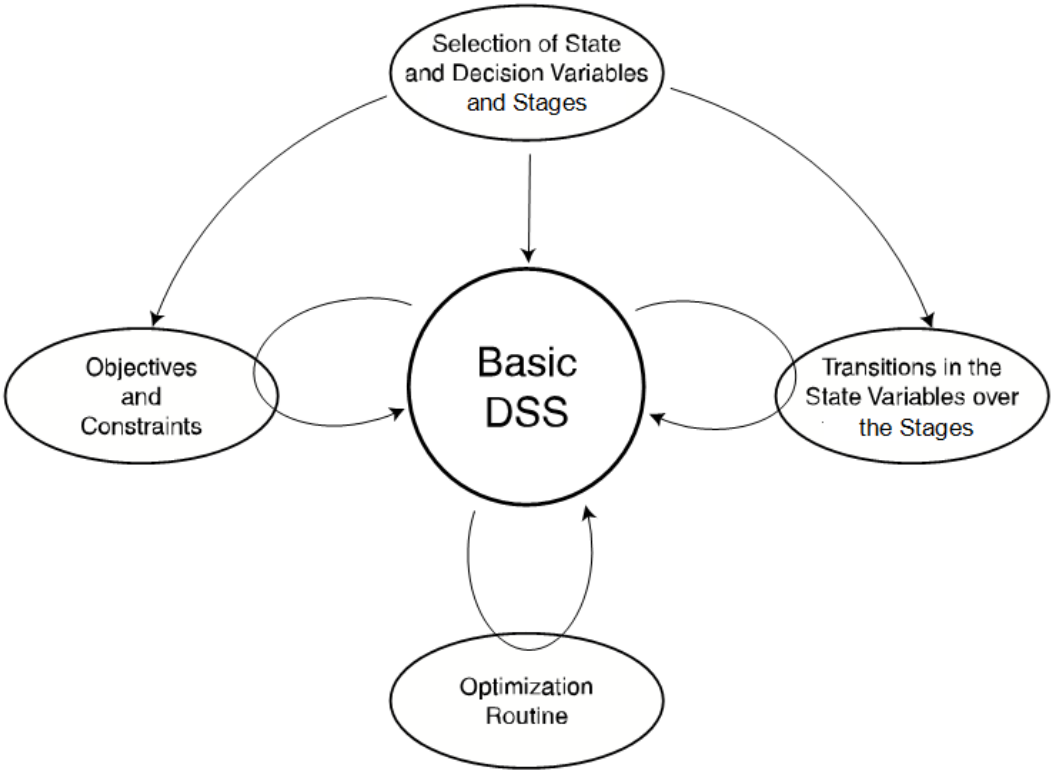


Figure 1.2: Decision Support System (DSS)
(Yang 2004.)

The third task is to specify the state transitions over the stages (stages). In some DP problems, the transitions are easily determined (e.g., water reservoir networks (Cervellera et al. 2002), inventory (Chen 1999)), However, pain management is a more complex application that requires estimation of the state transitions, similar to the ozone pollution application of Yang et al. (2007). A further complication for the pain management application is the dependence on a relatively small real data set. The ozone pollution application, by contrast, utilized a photochemical computer model to simulate air quality. Regression models are built to estimate state transitions and in addition, to estimate pain outcomes for the objective functions. Once all the above modeling is completed, the DSS will access an optimization routine to solve the DP problem via the Bellman backward recursion (Bellman 1957). Specifically, an approximate DP solution method based on a statistical perspective can be employed (Chen et al. 1999).

The remainder of this research is organized as follows. Chapter 2 provides the literature review on pain management and adaptive treatment strategies. The first section of chapter 2 gives the background of pain management. Section 2.2 discusses the adaptive treatment strategies that have been studied in health care. The third section of chapter 2 introduces the algorithm of stochastic dynamic programming (DP). Chapter 3 details the adaptive pain management DSS based on DP and some modeling results.

CHAPTER 2

LITERATURE REVIEW

2.1 Pain Management

Pain is commonly defined as an unpleasant sensation with an emotional component and can be present without tissue damage (D'Arcy et al. 2007). Pain management is a program that can achieve a targeted amount of reduction on pain outcomes to improve quality of life. The cost of pain is estimated at billions of dollars annually (D'Arcy et al. 2007). Pain can be categorized in many different ways. Most commonly, pain is classified to two types, acute and chronic pain, according to its duration (Gould 2007, Turk 2001 and Schatman & Champbell 2007). This research focuses on chronic pain.

Melzack and Wall (1965) first proposed the gate control theory that states pain experiences should consider physical and psychological factors. With better understanding of basic mechanisms for processing pain, the theories on pain have changed from single-cause to multi-causal explanations. Adjuvant therapies, which are designed for other medical conditions, have become alternatives for treating pain, instead of analgesics alone. Moreover, cognitive–behavioral or non-pharmacological treatments are introduced when a medication cannot manage pain or provide a desired level of pain relief (Gould 2007, Turk 2001 and Schatman & Champbell 2007).

Consequently, the multi-disciplinary or Interdisciplinary pain management program was proposed and has been demonstrated to be cost-effective for chronic pain. Such programs offer a broad choice of treatments and utilize a multiple discipline components, including biological and psychosocial factors. In current studies, biopsychosocial models have been applied successfully in chronic pain treatments instead of medical models (Schatman & Champbell 2007). Depending on the applied treatments for pain, patients will experience different levels of

pain in different ways at the time of diagnosis versus stages following treatment (Spanswick & Main 2000, Gould 2007 and Schatman & Champbell 2007).

2.1.1 Pain Type

Pain can be classified in various ways. It can be described according to the part of the body (e.g., headache, low back pain), tissue type, the way it is produced, or time. One of the common ways to classify pain is its duration. With the respect to time, depending on how long pain has been present, it is mainly categorized as acute or chronic pain. Acute pain is due to injuries of the body and persists for a short period of time until injuries are healed. The treatment for acute pain is to treat the injured portions of body and give analgesia. When injuries are recovered, acute pain will disappear. In contrast, chronic pain happens under any condition where pain has a long duration, over normal healing period of 3 to 6 months, or occurs from an isolated injury. It may be also caused by past injuries or diseases (Gould 2007, Ronen et al. 2006).

2.1.2 Cost of Chronic Pain

The cost of chronic pain has become an issue for society and health care resources. In the United States, the annual cost of chronic pain is estimated at $100 billion, including direct medical expenditures, informal costs, and lost productivity (Ronen et al. 2006, McCarberg & Passik 2005). One study even estimates that the direct and indirect costs of chronic pain can be $294.5 billion per year or even higher since this estimation does not consider utilization cost of health care for some co-morbid situations (Schatman & Champbell 2007).

2.1.3 Pain Management Programs

The goal of a pain management program is to help individuals with chronic pain to take back their quality of life. Early theories of pain transitions focus more on the physical side. Therefore, the traditional approach of pain management is to apply standard medical treatments, analgesics, to eliminate pain since it assumes that pain symptoms come from specific physical sources. Generally, doctors followed a standard process. First, they

investigated physical signs related to patients' symptoms to identify a specific diagnosis. Based on the diagnosis and their own clinical experiences, physicians identified treatable pathologies and then prescribed individual medical treatment plans to patients. Patients' physical signs and symptoms were expected to be cured after taking prescribed treatments (Spanswick & Main 2000, D'Arcy et al. 2007 and Schatman & Champbell 2007).

The idea of multi-disciplinary and interdisciplinary pain management was proposed to address cases of chronic pain that do not respond to the standard treatment of analgesics. Both use a biopsychosocial model for pain reduction. More specifically, interdisciplinary pain management is an extension of a multi-disciplinary approach. The difference between these two is their goals. Multi-disciplinary pain management involves a variety of specialists with independent goals. For interdisciplinary pain management, specialists all work together for setting one goal (Schatman & Champbell 2007).

2.1.4 Interdisciplinary / Multidisciplinary Pain Management

Current research demonstrates and suggests that pain management for chronic pain should consider relationships between physical responses, psychological responses, and emotions as treatment factors not just from the medical aspect. They indicate that sometimes problems are in a patient's mind if a patient's pain cannot be eliminated by prescribed medications. Moreover, a new concept was introduced. It is possible that pain can only be controlled or reduced but not eliminated. Therefore, cognitive–behavioral treatment or non-pharmacological treatments are introduced when a medication cannot manage pain or provide a desired level of pain relief. Cognitive–behavioral approaches emphasize how thoughts and beliefs can influence patients' pain outcomes and functional status to mediate their behavioral changes. Moreover, some medications have been discovered to provide better pain relief than analgesics (Schatman & Champbell 2007 and Gould 2007).

Today's interdisciplinary / multidisciplinary pain management programs integrate more elements from the psychological, emotional side. Furthermore, they also require more

commitment and responsibility from patients, and duration depends on each patient's progress. The treatment team for pain management usually consists of a physician, psychologist or psychiatrist, occupational therapist (vocational counselor), registered nurses, biofeedback therapist, social workers and various specialized physical therapists. Patients can choose where they want to complete treatment tasks, at home or in a clinic. Treatment tasks come from different aspects, such as relaxation, meditation techniques, stretching, aerobics, aquatic exercises, massage, and individual physical therapy (Spanswick & Main 2000, D'Arcy et al. 2007 and Schatman & Champbell 2007).

Many studies have illustrated the integration of interdisciplinary/multidisciplinary pain management programs to have promising effectiveness on different aspects. The result of sixty-five studies reviewed by Flor et al. (1992) supports the efficacy of multidisciplinary pain management centers. Kames et al. (1988) shows the great reduction on chronic pelvic pain by applying an interdisciplinary pain management program. Deardorff et al. (1991) present an outcome study on multidisciplinary chronic pain programs by comparing to a no-treatment group. In the study of Olason (2004), interdisciplinary pain management was implemented into a rehabilitation clinic, which focuses more on increasing patients' functioning and eliminating analgesics. With increasing numbers of cases applying cognitive–behavioral treatments, the reduction in pain, anxiety and depression was significant. Eccleston & Eccleston (2004) successfully applied physiotherapies within a cognitive behavioral framework. Vowles & McCracken (2010) even compare two different interdisciplinary pain managements for chronic pain.

To study the effects of various treatments on relevant outcome measures, this research employs the Robbins et al. (2003) database created by the Eugene McDermott Center for Pain Management at the University of Texas Southwestern Medical Center at Dallas. This database studies a two-stage treatment program for interdisciplinary pain management. Patients are

evaluated pre-treatment (pre), midpoint (mid) after the first stage of treatment, post-treatment (post) after the second stage of treatment and one-year following completion of the program.

The raw dataset has complete outcome data over pre, mid, and post for 120 patients from August 1998 to May 2001. The elapsed time between pre and mid evaluation ranges from several weeks to more than 6 months. Before the first stage of treatment, each patient was pre-evaluated based on treatment background and pain symptoms and severity, including a detailed review of medical records, a physical examination, psychological profile, and level of physical conditioning. Upon completion of the first stage of treatment, each patient is evaluated midpoint in the program. Depending on the result at the midpoint, a second stage of treatment is assigned. Upon completion of the second stage of treatment, each patient is post-evaluated.

2.1.5 Treatment options

For the patients with chronic pain, not only do their treatments selections vary, but also their intensity and duration of treatment plans, costs and follow-up plans. With the understanding of basic mechanisms for processing pain during the past decade, adjuvant therapies, which are designed for other medical conditions, have become alternatives for treating pain instead of using analgesics along. Additionally, non-pharmacological treatments and cognitive techniques are used when a medication cannot manage pain or provide a desired level of pain relief (Gould 2007 and D'Arcy et al. 2007). The options of pain treatment are listed below (Warncke et al. 1994, Zaza et al. 1999, Dalton and Youngblood 2000, Davies McVicar 2000 and Gould 2007).

a. Pharmacological therapies – Analgesics

1. Non-opioid – Nonsteroidal anti-inflammatory drugs (NSAIDs, e.g., acetaminophen, aspirin, ibuprofen); Paracetamol; Corticosteroids (e.g., dexamethasone)
2. Weak opioid (e.g., codeine, hydrocodone, dihydrocodeine, propoxyphene, tramado,)

3. Strong opiod (e.g., fentanyl, hydromorphone, levorphanol, methadone, morphine, oxycodone, pentazocine, meperidine, buprenorphine, pentazocine, nalbuphine)

b. Pharmacological Adjuvant Therapies

1. Alchohol
2. Anticonvulsants (e.g., cabamazepine, diazepam, phenytoin, valproic acid)
3. Antidepressants (e.g., amitriptyline, imipramine, trazadone)
4. Anxiolytics
5. Coricosteroids
6. Muscle Relaxers (e.g., soma, flexeril, norflex)
7. Neuroleptics (e.g., chlorpromazine, levomepromazine or methotrimeprazine)
8. Benzodiazepines (e.g., sedatives: valium, ativan, versed)
9. Local Anesthetics (e.g., local, topical, systemic)
10. Eutectic Mixture of Local Anesthetics (EMLA)
11. Lidoderm Patch
12. Subcutaneous Continuous Infusion

c. Non-pharmacological Adjuvant Therapies

1. Physical relaxation strategies (e.g., acupuncture / acupressure, chiropractic, cold or heat therapy, massage, therapeutic touch)
2. Psychological strategies (e.g., autogenic training, biofeedback, cognitive therapy, hypnosis, individual psychotherapy, meditation, music or art therapy, operant conditioning, progressive muscle relaxation, support groups, visualization or imagery)
3. Medical interventions (e.g., anaesthetic blocks, radiotherapy / radiation, surgery, transcutaneous electrical nerve stimulation)

2.1.6 Outcome measurements / Pain assessment

There are number of resources in measuring pain. They can be classified as single dimensional/one-dimensional or multidimensional measurements. One dimensional pain scales are not only the traditional measures of pain intensity but are also the most common ones used to evaluate patients' pain in clinics. In single dimensional pain scales, the visual analog scale (VAS), verbal descriptor scale (VDS) and numerical pain scales (NPS) are most often used. However, multidimensional measurements were proposed because one dimensional measurement cannot detect motivational-affective dimensions of pain (Raj 2003, D'Arcy 2007 and Turk & Melzack 2001). There are 6 dimensions in the multidimensional measurements – sensory, affective, cognitive, physiologic, behavioral and sociocultural *(McGuire 1992 and Cady 2001)*. The first three were introduced by *Melzack and Wall (1965, 1982,1988); the last three were proposed by Ahles et al. (1983) and McGuire (1987).* In the multidimensional measurements, the brief pain inventory (BPI) and short form McGill pain questionnaire (SF-MPQ) are most often used. *The outcome measurements of pain are listed below:*

a. Unidimensional measurements
    1. Visual analog scale (VAS, Raj 2003, D'Arcy 2007)
    2. Verbal descriptor scale (VDS, Raj 2003, D'Arcy 2007)
    3. Numerical pain scales (NPS, Raj 2003, D'Arcy 2007)
    4. 11-point box scale (Raj 2003)
    5. 101-pint numerical rating scale (Raj 2003)
    6. 4-point and 5-point verbal rating scale (Raj 2003)
    7. Graphic Rating Scale (GRS, Huskisson 1974, Heft and Parker 1984)
    8. Color Scale (Dalton and McNaull 1998)
    9. Verbal Descriptor Scale (Melzack and Torgerson 1971, Scott and Huskisson 1976, Dalton et al. 1988)
    10. Picture Scale (Frank et al. 1982, Wong and Baker 1988)

11. Self-Monitored Pain Intensity (Kerns et al. 1988)

b. Multidimensional measurements

1. Brief pain inventory (BPI, Raj 2003, D'Arcy 2007)
2. McGill pain questionnaire (MPQ): Short form (SF-MPQ, Melzack 1987, Raj 2003) and long form (Melzack 1975)
3. Pain disability index (Raj 2003)
4. Neck disability index (Raj 2003)
5. Dallas pain questionnaire (Raj 2003)
6. West Haven-Yale multidimensional pain inventory (Raj 2003)
7. Descriptor differential scale (Raj 2003)
8. Wisconsin brief pain questionnaire (Raj 2003)
9. Sickness impact profile (Raj 2003)
10. Abu-Saad pediatric pain assessment (Raj 2003)
11. Pain Assessment Tool and Flow Sheet (McMillan et al. 1988)
12. Body Chart (Twycross and Lack 1983)
13. Memorial Pain Assessment Card (Fishman et al. 1987)
14. Pain/Comfort Journal (Keating and Kelman 1988)
15. Chronic Pain Experience Instrument (Davis 1989)

2.1.7 Guidelines / Standards

In order to treat pain properly, many health organizations have started to setup standards or guidelines for pain management. The first effort is from the Agency for Health Care Policy and Research (AHCPR). It provides guidelines for acute pain, cancer pain, and low back pain. Then, the American Pain Society (APS) took over the development of guidelines for pain management in specific populations. Furthermore, many national specialty organizations have their own pain management guidelines for their specific patients' population. One of the strongest national guidelines is the Joint Commission on Accreditation of Healthcare

Organizations (JCAHO). Its guidelines direct the practice of pain management in all hospitals (D'Arcy et al. 2007).

For general principles, the World Health Organization (WHO) developed straightforward guidelines for the treatment of cancer pain in 1986, called the analgesic three steps ladder (Figure 2.1). Today, the guidelines of the pain ladder are not only used for cancer pain but also for all types of pain models in pain management. The general guidelines of pain management start from the bottom of ladder with a non-opioid analgesic and adjuvant therapies. If pain becomes mild or moderate, a patient should move to middle ladder step and be given a weak opioid plus non-opioid analgesic and/or adjuvant therapies. When pain continues or worsens, the next step is a strong opioid plus non-opioid analgesic and/or adjuvant therapies for moderate and severe pain at the top of ladder (Dalton and Youngblood 2000).

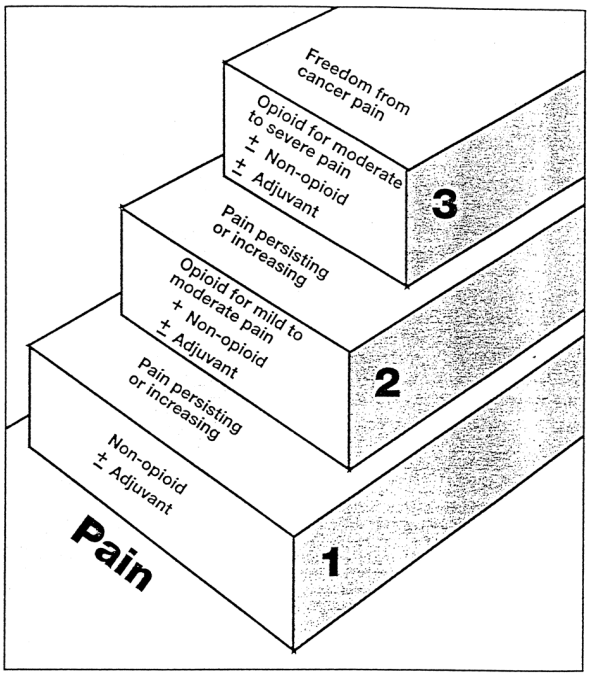


Figure 2.1 The World Health Organization's Analgesic Ladder Approach for Relief of Cancer Pain. (Dalton and Youngblood 2000).

2.2 Adaptive Treatment Strategies

In medical research, adaption or adjustment is usually accomplished by employing available treatments. With a wide variety of available treatments, physicians can continually adapt and readapt treatments to patients for acute responses. One question arises – How can available treatments be assigned sequentially for the optimal outcome? Adaptive treatment strategies are a set of decision rules or treatments in which patients are treated sequentially based on their characteristics and heterogeneous responses over multiple stages. The term "adaptive treatment strategies" is also referred to as dynamic treatment regimes, adaptive interventions, or tailored communications (Murphy 2003, Murphy et al. 2007).

Research on adaptive treatment strategies is growing. Dawson & Lavori (2003) applied two different adaptive treatment strategies, baseline and adaptive randomization, for a major depressive disorder. Hernάn et al. (2006) presented the comparison of two dynamic treatment regimes to acquired immunodeficiency syndrome (AIDS)-free survival in a study of human immunodeficiency virus (HIV)-infected patients. Rivera et al. (2007) introduced several engineering control principles to improve the design of adaptive interventions in the chronic treatment of substance abuse. This research focuses more on the mapping of adaptive treatment strategies.

Adaptive treatment strategies have been successfully implemented by employing different algorithms in a diversity of health care research. Depending on the applied approaches, this research can be divided into two categories: randomized experimentation and Markov decision process. Randomized experimentation, addressed in section 2.2.1, includes the multiphase optimization strategy (MOST) and sequential multiple assignment randomized trials (SMART). Markov decision processes (MDP) are discussed in section 2.2.2. Specific applications of randomized experimentation and MDP are also discussed. Both categories are related to stochastic dynamic programming (SDP), which is employed in this dissertation to

develop an adaptive treatment strategy for an interdisciplinary pain management program. In the section 2.3, stochastic dynamic programming (SDP) is discussed.

2.2.1 Randomized Experimentation

The multiphase optimization strategy (MOST) and sequential multiple assignment randomized trials (SMART) apply randomized experimentations to achieve valid inferences. In MOST, factorial analysis of variance (ANOVA) is used to efficiently define its important components; in SMART, experimental trials are organized to develop decision rules (Collins et al. 2007).

2.2.1.1 Multiphase optimization strategy (MOST)

In traditional intervention development, interventions are constructed first and then interventions are evaluated in a standard randomized controlled trial (RCT), which is a randomized allocation for different interventions. However, RCT treats interventions as a whole, and does not isolate effects of individual components. The multiphase optimization strategy (MOST) was proposed by Collins et al. (2007). It is not only an alternative approach of a standard RCT but also incorporates the standard RCT. It has three phases: a screening phase, a refining phase, and a confirming phase. Before the screening phase, all possible components should be categorized to program components and delivery components. In the screening phase, all possible components are included in an intervention and then active components are identified by employing randomized experimentation through factorial analysis of variance (ANOVA).

In the refining phase, the objective is fine tuning, so as to examine the optimal level of identified active components from the screening phase by employing randomized experimentation through ANOVA, response surface experiments or sequential multiple assignment randomized trials (SMART). Moreover, this phase investigates the interaction effects among the identified components and their interrelationships with covariates. Briefly speaking, this step decides the optimal dosage level and combinations of components. The final

step, a confirming phase, is to evaluate and confirm the optimized intervention from the identified components with optimal levels in the refining phase through RCT. Figure 2.2 briefly shows the process of MOST (Collins et al. 2005 and Collins et al. 2007).

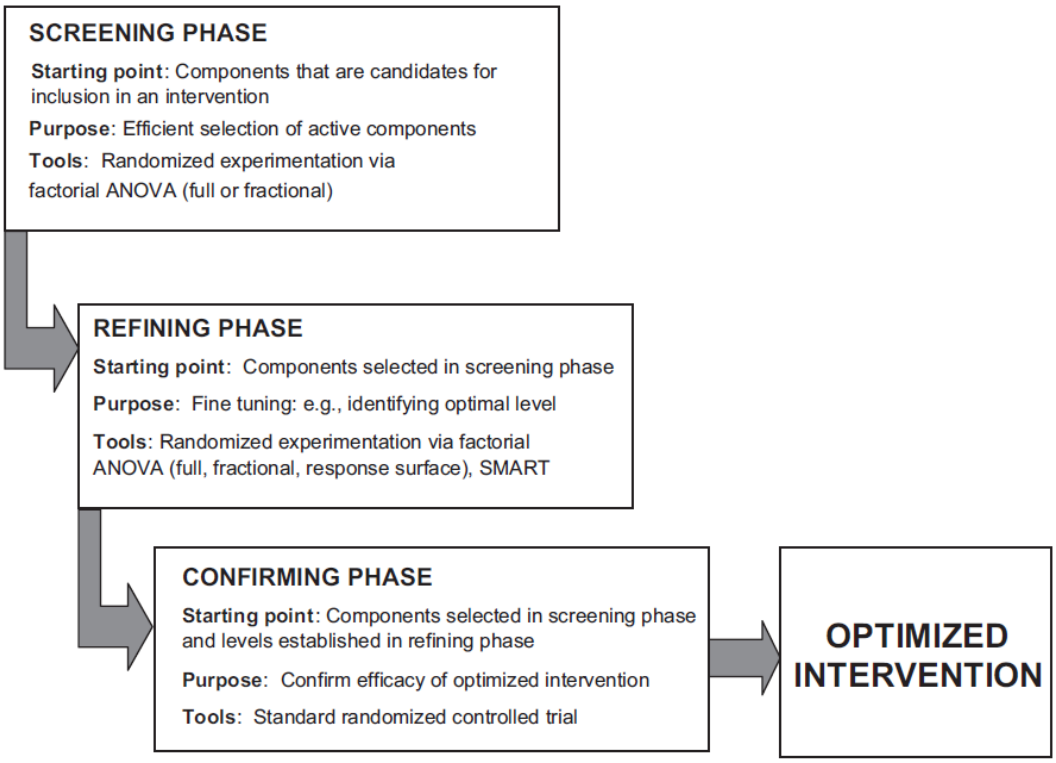


Figure 2.2 Outline of the Multiphase Optimization Strategy (MOST). ANOVA, analysis of variance; SMART, sequential multiple assignment randomized trial. (Collins et al. 2007)

Collins et al. (2007) addresses a hypothetical case of smoking cessation to illustrate MOST. In this case, six components, in which the investigators are interested, are identified: outcome expectation messages, efficacy expectation messages, message framing, testimonials, exposure schedule and source of message. In the screening phase, it is determined which component should be included or dropped from the intervention. After a randomized experimentation to isolate the effects of each six components, supposedly the result shows the active components are outcome expectation messages, efficacy expectation messages, testimonials and exposure schedule. Proceeding to the refining phase, the

investigators determine the best level of six components and assume there are no important interaction effects among these components via experimental design techniques. In the confirming phase, the intervention consisting of six components and their optimal levels can be evaluated by RCT.

2.2.1.2 Sequential multiple assignment randomized trials (SMART)

The Sequential multiple assignment randomized trials (SMART) approach was proposed by Murphy (2005). The goal of SMART is to refine adaptive treatment strategies. It uses experimental trials to develop the decision rules in adaptive treatment strategies. It has been successfully applied in many different medical applications, such as the study of Schneider et al. (2001) on antipsychotic medications in patients with Alzheimer's; the studies of Rush et al. (2003) and Lavori et al. (2001) on Sequenced Treatment Alternatives to Relieve Depression (STAR*D); the research of Stone et al. (1995) and Tummarello et al. (1997) on cancer treatment of Phase II trials at MD Anderson.

In adaptive treatment strategies of clinical areas, normally decision rules or recommendations of treatment changes are based on patients' variables. Patients' variables can be their characteristics, family history or various types of outcome measures. In the case of SMART, the decision rules are randomly given by possible treatments at each decision point (Murphy et al. 2007).

Murphy et al. (2007) gives an alcohol-dependent case as an example. In this case, the decision rules adapt treatments depending on their heavy drinking days and side effects. First, patients are given an opiate antagonist Naltrexone (NTX) and medical management for 2 months. Within this stage, if patients only have 1 heavy drinking day, they are provided a prescription of NTX and Telephone Disease Management (TDM); If they have 2 or more heavy drinking days with minimal side effects to NTX, they are provided NTX and Combined Behavioral Intervention (CBI); If they have 2 or more heavy drinking days with moderate or severe side effects to NTX, they are given CBI only.

In the case of SMART, similarly, first patients receive NTX and medical management for 2 months. If they only experience 1 heavy drinking day within 2 months, they are randomly prescribed to either NTX or NTX plus TDM; If they experience 2 or more heavy drinking days, they are randomly prescribed to either NTX plus CBI or CBI only; If they experience 5 or more heavy drinking days, again they are randomly prescribed to either NTX plus CBI or CBI only. The evaluation of randomized trials shows two results. One is no difference between patients with NTX and NTX + TDM, and patients with CBI + NTX have better outcomes than the ones with CBI only. Based on these results, the decision rules can be redefined. Patients first receive NTX treatment within 2 months. If they only have 1 heavy drinking day, they are prescribed NTX treatment; if they have 2 or more heavy drinking day, they are prescribed CBI + NTX; if they have 2 or more heavy drinking day and substantial side effects, they are prescribed CBI only (Murphy et al. 2007).

2.2.1.3 Instance-based Reinforcement Learning

Pineau et al. (2007) construct adaptive treatment strategies from randomized trials via a computer science methodology, called instance-based reinforcement learning. In the field of computer science, reinforcement learning first started in trial-and-error learning and is widely used in sequential decision-making and time varying systems, especially for data from randomized multiple, sequential trials. Therefore, Pineau et al. (2007) demonstrated examples with the data from an application of SMART, the STAR*D trials.

Reinforcement learning incorporates the concept of reward and value. The treatment with higher value will be chosen. The value of treatment consists of the reward for using the treatment and the reward later using the best possible treatment sequence. If a patient arrives, the method of instance-based reinforcement learning searches the databank from STAR*D to find patients with similar characteristics and selects decision rules among these with the highest values (Pineau et al. 2007). It should be noticed that reinforcement learning is a method to solve the SDP. In this case, it uses the data from randomized trials.

2.2.2 Markov Decision Process

Markov decision processes (MDPs) are appropriate tools for making sequential medical treatment decisions under uncertainty. There are several applications that have successfully implemented MDPs. Exact MDPs solutions have been proven optimal, however, they have disadvantages with regard to the size of problems and the quality of data. Larger problems are exponentially harder to solve, and sufficient data is needed to compute transition probabilities for each stage (Scheafer et al. 2004). In this section, basic information on MDPs is introduced, and two health care applications are presented.

Generally speaking, there are four fundamental types of MDPs, finite-horizon MDPs, infinite-horizon MDPs, partially observed MDPs (POMDPs) and semi-MDPs (SMDPs). There is a standard assumption of MDPs, that is the future transitions and rewards are independent of the past states and actions. MDPs are typically discrete-time processes. At each stage of a process, an available action/decision can be taken for a given state, which completely encompasses required information for future decisions. Then, a reward or cost is received, and the process transition to a new state. Transitions to future states are model probabilistically. Finite-horizon MDPs have a finite number of stages. Infinite-horizon MDPs are used when the number of stages cannot be specified. They are commonly employed when the system is time-homogeneous or changing very slowly, and can be solved by policies iterations. POMDPs can be applied to obtain the optimal policy when the state only has imperfect information from the observations of the system and previously applied decision rules. The partially observed state can be replaced if there are sufficient statistics of the true state. SMDPs are used when the time between decisions varies probabilistically. For more comprehensive coverage, we would like to refer the chapter 23 of Scheafer et al. (2004), which describes more applications in. The following sections describe two examples.

2.2.2.1 Liver Transplantation Example

Alagoz et al. (2004) structure a discrete-time, infinite-horizon, discounted MDP model to optimize patient quality-adjusted expectancy for liver transplantation using clinic data. They also incorporate the risk and reward of re-transplantation into the probability of death during the transplant operation. Patients' health represents the state of the process. Transition possibility and reward functions are assumed stationary. In their model, the decision can be one of two actions, transplant or wait, for a given state.

If the action is "transplant" in a health state, the patient receives a total expected discounted post-transplant reward, quits the process and moves to the "transplant" state with probability one. The post-transplant reward is equal to the expected life days of the patient, given the health status at the time of the transplant and the liver quality. If the action is "wait" in a health state, the patient receives one day as a intermediate reward, accrued in the current stage and moves to the next state according to a probability transition matrix (Alagoz et al. 2004).

Alagoz et al. (2004) used the policy iteration algorithm for the solution of this MDP application and its optimal stationary policy, which is the control-limit type. The optimal policy is to maximize the patient's total reward from pre-transplant and post-transplant reward and not just to maximize one of two components. In other words, it is to determine the optimal time for living-donor liver transplantation.

2.2.2.2 Breast Cancer Example

Chhatwal (2008) provides a quantitative guideline to assist radiologists for mammography, so that they can have more information based on mathematical frameworks to determine the timing on patients' biopsy and short-interval imaging follow-up for breast cancer diagnostics. For each mammography visit, a woman has three options – biopsy, wait until the next annual mammography, or follow-up procedures. The decision is determined by her current risk of breast cancer, evaluated by risk prediction models or a radiologist. After a biopsy, the

patient is out of system and will become a new case when she visits again. The patients and decision makers are risk neutral.

This research applied a series of finite-horizon, discrete-time MDPs to seek optimal decision policies for early breast cancer patients. It derived three different models of MDPs and further developed new structure properties of MDPs for this specific problem. The three models consist of a two-decision problem (biopsy vs. routine annual mammogram), an extension of the two-decision problem (adding another option, short-interval follow-up), and a three-decision problem (biopsy, short-interval follow-up or annual mammogram). The objective of these MDPs is to maximize the expected adjusted-quality life years by providing the optimal decision policy. The objective of their research was to save unnecessary over-treatments recommended by radiologists. For comparison, this research used the real-life mammography data in their clinical practice at Medical College of Wisconsin, Milwaukee from 1999-2004 for the optimal decision policies of MDPs and compared those policies with the decisions made by radiologists. Their result did show the number of biopsies should be less than what was recommended by those guidelines (Chhatwal 2008).

2.3 Stochastic Dynamic Programming (SDP)

Stochastic Dynamic Programming (SDP) is an optimization approach for multi-stage problems and has been applied for solving problems in a various types of systems such as manufacturing systems, finance, environmental engineering and others (White 1985, 1988, Scheafer et al. 2004 and Yang 2004). It can model a system changing over time and can be used to solve MDPs. There are several components in SDP. State variables detail the states of system at each stage. Decision variables are the ones that decision maker can control to minimize expected current and future costs. Transition functions identify how the state changes from the current stage to the next stage. The optimal solution can be solved via a backward recursion algorithm. At each stage of system, after the optimal expected current and future costs are calculated over all possible current states and stored as the future (or optimal) value

function. This can be computationally-intractable is the state space is very large. In particular, continuous-state DP has infinite state spaces; hence, interpolation over a discretized the state space has been used to approximate the continuity of system (Chen 1999).

2.3.1 Continuous-State DP

In a continuous-state SDP, state and decision variables are all continuous as the case of ozone pollution (Yang 2004). The pain management SDP application has a mix of continuous and discrete (binary and categorical) variables. The prototype in this dissertation models all variables as continuous, since methods to appropriately handle this mix of variables are still under development. A finite-horizon, continuous-state SDP model is described as follows (Chen et al. 1999):

$$min\, E\left\{\sum_{t=1}^{T} c_t(x_t\,, u_t\,, \varepsilon_t\,)\right\} \tag{2.1}$$

$$s.t.\, x_{t+1} = f_t(x_t\,, u_t\,, \varepsilon_t), for\; t = 1, \dots, T-1$$

$$(x_t\,, u_t) \in \Gamma_t\,, for\; t = 1, \dots, T\,.$$

In equation 2.1, *T* represents the total numbers of stages; x_t is the state vectors where $x_t \in R^n$ and describes the state of system; u_t represents decision vectors where $u_t \in R^m$ and is the only vector we can control to minimize the current plus future cost; $c_t(\cdot)$ defines the cost function for period *t* where $c_t(\cdot)$: $R^{n+m+1} \rightarrow R^1$; $f_t(\cdot)$ is the transition function from stage *t* to *t*+1; ε_t is the random vector where $\varepsilon_t \rightarrow R^1$; Γ_t is the set of constraints where $\Gamma_t \subset R^{n+m}$. A future value function at stage *t* can be defined as equation 2.2; a recursive future value function at stage *t* is defined as equation 2.3 (under that same constraints as 2.2):

$$F_t(x_t) = \min_{u_t \dots u_T} E\left\{\sum_{\tau=t}^{T} c_\tau(x_\tau\,, u_\tau\,, \varepsilon_\tau\,)\right\} \tag{2.2}$$

$$s.t.\, x_{\tau+1} = f_\tau(x_\tau\,, u_\tau\,, \varepsilon_\tau), for\; \tau = t, \dots, T-1$$

$$(x_\tau\,, u_\tau) \in \Gamma_\tau\,, for\; \tau = t, \dots, T$$

$$F_t(x_t) = \min_{u_t} E\{c_t(x_t, u_t, \varepsilon_t) + F_{t+1}(x_{t+1})\}, \quad t = 1, \ldots, T. \tag{2.3}$$

The traditional way for solving continuous-state SDP is to discretize the state space, using for example a regular finite grid, solve for the optimal solution at each discretization point, then use interpolation or some functional approximation schemes to provide a continuous approximation of the future value function Foufoula-Georgiou et al. (1988), Johnson et al. (1993) and Chen et al. (1999). Traditional methods of discretization, as used by Foufoula-Georgiou et al. (1988) and Johnson et al. (1993), are limited by the curse of dimensionality for which the number of points increases exponentially as the number of variables grows linearly. Chen et al. (1999) applied statistical experimental design and statistical modeling to mitigate this exponential growth in computational effort.

2.3.2 Algorithm for Solving High Dimensional Continuous-State SDP

Chen et al (1999) proposed an SDP solution method, which used experimental design to discretize the state space and Multivariate Adaptive Regression Splines (MARS) to approximate future value function. It is described in Figure 2.3. The first step is to choose the method of experimental design in order to discretize the state spaces of the given stage *t*, for *t* = 1, ...,T (Yang 2004). For the adaptive pain management DSS, a Latin hypercube (LH) experimental design with 50 points is used. A brief review of Latin hypercube (LH) experimental design will be given in section 2.3.3.2.

Since an SDP solution approach solves backwards, the step 2(a) obtains values on the future value function at the last stage *T*, which can be solved by minimizing the expectation taken over the random vector ε_j, for a given discretization point x_{jT}. Transition functions and stochastic components of pain management problem will be addressed more detail in chapter 3. The step 2(b) uses a statistical modeling method to fit the data from step 2(a) to construct the continuous approximation of the future value function. Chen et al. (1999) and Yang (2004) used MARS to approximate the future value function. Cervellera et al. (2006, 2007) and Fan (2008)

used Artificial Neural Networks (ANNs). ANNs are employed in this dissertation for the adaptive pain management SDP is and will be discussed in section 2.3.4.

Recursively for the other stages, step 3(a) conducts the same task as step 2(a), and step 3(b) approximates the future value function as in step 2(b). The future value function from the first stage holds the solution for the entire horizon.

1. Choose *N* discretization points in the state space $\{x_{jt}\}_{j=1}^{N}$ for the *t*-th stage, $t = 1, \dots, T$, and $x_{jt} \in R^n$.
2. In the last stage *T*,
   a) For each discretization point x_{jt}, $j = 1, \dots, N$, solve
      $$F_T(x_{jT}) = \min_{u_{jT}} E\{c_T(x_{jT}, u_{jT}, \varepsilon_j)\},$$
   b) Then approximate $F_T(x_T)$ with $\hat{F}_T(x_T)$, for all $x_{jt} \in R^n$, using the data for F_T from step 2(a).
3. In each stage $t = T-1, \dots, 1$,
   a) For each discretization point x_{jt}, $j = 1, \dots, N$, solve
      $$\tilde{F}_t(x_{jt}) = \min_{u_{jt}} E\left\{c_t(x_{jt}, u_{jt}, \varepsilon_t) + \hat{F}_{t+1}\left(f(x_{jt}, u_{jt}, \varepsilon_t)\right)\right\},$$
   b) Then approximate $\tilde{F}_t(x_t)$ with $\hat{F}_t(x_t)$, for all $x_t \in R^n$, as in step 2(b).

Figure 2.3 A general algorithm for solving continuous-state SDP models (Chen et al. 1999).

2.3.3 Statistical Methods for Computer Experiments

To design a complex system, the most practical solution is computer experiments. In engineering it is common to build a simulation model to study how a complex system performs and operates. In simulation models, system parameters need to be specified in order to optimize system performance. However, when a simulation model has many parameters and/or is computationally expensive, a outcome model can be constructed as a surrogate in an iterative optimization approach. A outcome model is a "model of a model" and is based on data collected from a computer model. The outcome model is a closed form approximation of the relationship between output and input variables (Chen et al. 2003). In the case of SDP, the

computer model is not a simulation model, but instead it is the optimization that is conducted in each stage.

2.3.3.1 Design of Experiments

Scientists use experiments to study something unknown in a system or process, typically with one output and several inputs. Design of Experiments was developed by statisticians to organize efficient experiments (Montgomery 2005). Good experimental designs efficiently select design points in the explanatory/input variable space to attain data that can enable estimation of desired effects on a response/output variable and determine the statistical significance of the inputs. For computer experiments, appropriate experimental designs "fill" the input space (Chen et al. 2006). The discretization of state space in for continuous-state SDP problem is essentially an experimental design for a computer experiment. Chen et al. (2006) describe several experimental design and statistical modeling options for computer experiments. In this dissertation, we only review Latin hypercube designs, in the next section, and ANNs in section 2.3.4.

2.3.3.2 Latin Hypercube Design and Sampling

Latin hypercube sampling was proposed by McKay et al. (1979) in the context of Monte Carlo simulation. A Latin hypercube is special subset of a full grid, and the sampling component randomly perturbs the points of a Latin hypercube. The special property of Latin hypercubes with n points is that when projected only any single dimension, n distinct values (levels) are represented. Figure 2.4 shows the algorithm for generating a Latin Hypercube design with size n. There are d variables/dimensions with n levels for each variable. All d variables are divided into n intervals. The size of intervals need not be equal. Latin hypercube designs are not guaranteed to be orthogonal (uncorrelated), so the correlations between variables should be verified to be low (Yang 2004).

(1) For each dimension $j = 1, \ldots, d$: initialize $Qj = \{1, \ldots, n\}$.

(2) For each design point $i = 1, \ldots, n$:

  (a) Randomly sample vj from Qj, for $j = 1, \ldots, d$.

  (b) Let $Qj = Qj - \{vj\}$, for $j = 1, \ldots, d$.

  (c) Assign design point i : level vj for dimension j, for $j = 1, \ldots, d$.

Figure 2.4 Algorithm for generating a Latin Hypercube design (Chen et al. 2006)

2.3.4 Approximating Future Value Functions Using Statistical Modeling

There are several statistical algorithms which can be employed for computer experiments for the approximation of the future value function such as response surface models, multivariate adaptive regression splines (MARS), and artificial neural networks (ANN). MARS was applied in inventory forecasting problems (Chen et al. (1999), Chen (1999)), a wastewater treatment application (Tsai et al. 2004, Tsai and Chen 2005) and the ozone pollution application of Yang et al. (2007). In water reservoir management applications, Cervellera et al. (2006, 2007) implemented ANN as an alternative of MARS. In the pain management case, the approach of artificial neural networks (ANN) method is applied and reviewed below.

Artificial Neural Network (ANN) modeling was inspired by biological nervous systems as an approach to "learn" systems. It has been widely applied in the various aspects of science and engineering (Haykin 1999). The architecture of an ANN is composed in layers of nodes with arcs connecting nodes. In a feedforward ANN, the first layer is the input layer with each node representing an input variable, and the last layer is the output with each node representing an output variables (where ANNs can easily accommodate multiple output variables), and information along arcs only flows in the direction of input to output (arcs cannot exist within the same layer). In between are "hidden" layers where a larger number of hidden layers increase

the flexibility of the model. However, in practice, it has been found that one hidden layer in a feedforward ANN is often sufficient for function approximation. Within each hidden layer, there are hidden nodes, where a larger number of hidden nodes increase the flexibility of the model. In the selection of the appropriate ANN architecture for function approximation, the most difficult choice is the number of nodes in the hidden layer. At each node, the information received from nodes in the previous layer is transformed via an activation function before being passed on to nodes in the next layer. For function approximation it is recommended to employ sigmoidal activiation functions. ANNs can model a wide variety of relationships and a comprehensive presentation may be found in Haykin (1999).

Cervellera et al. (2007) illustrates that ANNs perform comparably to MARS for the approximation of future value function of SDP. The comparison in Cervellera et al. (2007) demonstrates that MARS and ANN both have the similar structure from stage to stage. The use of ANNs for the adaptive pain management DSS could provide better representation of binary/categorical in future work.

CHAPTER 3

ADAPTIVE PAIN MANAGEMENT DECISION SUPPORT SYSTEM

In this dissertation, a prototype for adaptive pain management based on stochastic dynamic programming (SDP) is developed. Its purpose is to provide decision support for improving pain outcomes and attaining targets in a two-stage interdisciplinary pain management program.

The goal of adaptive strategies for pain management is to minimize treatment cost and patients' pain outcomes via a decision support system (DSS). As described in section 1.2, there are four tasks for the adaptive pain management DSS. The first task is to specify the state and decision variables and stages. The second task is to identify the cost objectives and constraints. The third task is to specify the state transitions over the stages (stages). The last task is to optimize the decision variables with an appropriate routine.

In this chapter, section 3.1 covers the data preparation which includes the basic components of DP, stages, state variables, decision variables and outcome measures. Moreover, it also talks about some issues on handling the raw dataset. Section 3.2, describes how to formulate the SDP model for the pain management program, including the treatment cost function and penalty function.

Figure 3.1 shows our entire approximate DP process. It begins with data preparation and then builds models for the outcomes and state transitions via regression models. The set of potential state variables for the pain management study is over 200, which is very high-dimensional for DP. As in Yang et al. (2007), the regression models provide dimension reduction, as well as approximations. Given the set of state and decision variables that must be maintained for the modeling, the DP solution approach from Chen et al. (1999) employs

experimental design techniques and statistical modeling (e.g., artificial neural networks) to approximate the future value function.

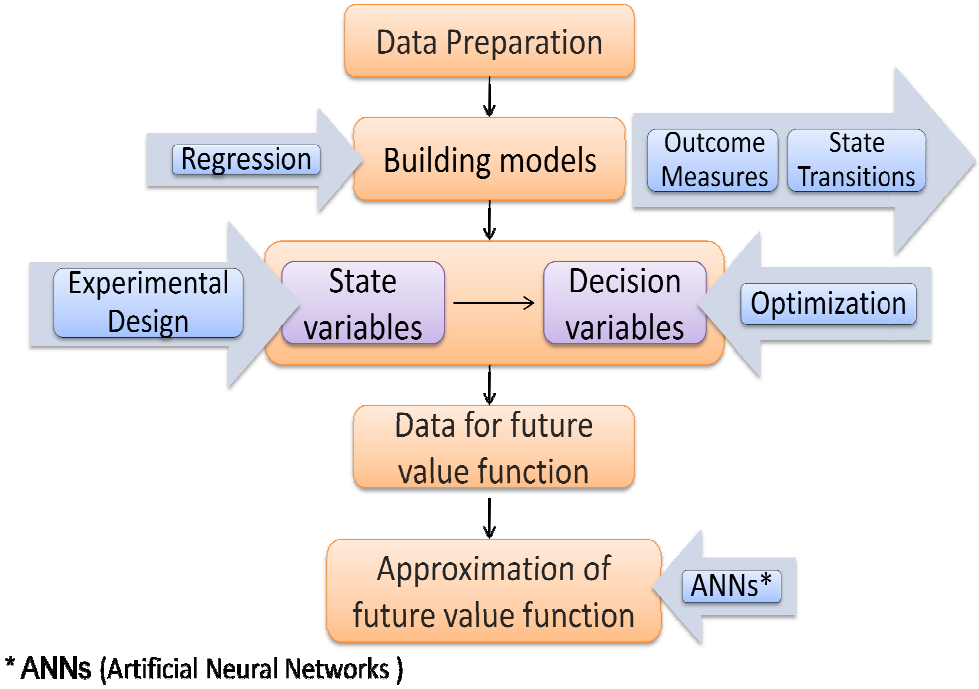


Figure 3.1: Approximate DP Process for the Pain Management DSS

3.1 Data Preparation

This section describes the basic information of dataset and how stages, state variables and decision variables are identified for the modeling. The raw dataset, referred to as the Robbins et al. (2003) data base, was provided by the University of Texas Southwestern Medical Center at Dallas. It contains data on 127 patients across over 200 variables in the medical center's interdisciplinary pain management program. Following the structure of their program, there are two stages modeled in this application; patients' background information is included as the state variables, such as age, gender, surgical and physical histories, and past diagnoses; and treatment options are selected as the decision variables.

Unfortunately, there were many missing data or invalid values among the observations. If all observations with missing data were dropped from the model, there would not be enough observations for modeling. Moreover, among the 42 treatments, not all of them were prescribed

during the study period. To preserve the use of as much data as possible, many missing and invalid values were imputed via regression models. To accommodate the different types of treatments, they were grouped based on similarity of function, so that there were no zero counts for any group. The final cleaned dataset contained 89 observations with 70 variables and various outcome measures.

The following sub-sections detail the pre-evaluation information, treatment options, and outcome measures collected in the Robbins et al. (2003) database. In particular, sections 3.1.4-3.1.7provides data counts and groupings that were necessary to avoid empty cells (i.e., zero counts) when conducting the analysis. Section 3.1.8 re-specifies the 70 variables in the final cleaned dataset. Section 3.1.9 state the detail of our outcome measurements.

3.1.1 Variables for Patients' Background

The variables describing patients' background consist of 38 for patient's surgical history (Table 3.1), 25 for physical history (Table3.2), 26 for patient's diagnosis (Table 3.3) and 13 other variables (Table 3.4). This information is collected when a patient initiates the pain management program. The abbreviations and descriptions of these variables are listed as below (Column 1 is the field name in the database. Column 2 is the description in the database):

Table 3.1 38 Types of Patients' Surgical Histories

Variables	Description	Variables	Description
surghx1	Unspecified discectomy	surghx20	Neural decompression, other
surghx2	Microdiscectomy	surghx21	Fracture-dislocation: closed reduction
surghx3	Percutaneous discectomy	surghx22	Fracture-dislocation, open reduction
surghx4	Chemonucleolysis	surghx23	Pseudoarthrosis repair (same with surghx10)
surghx5	Unspecified fusion	surghx24	Hardware Removal
surghx6	Anterior fusion	surghx25	Amputation
surghx7	Posterior interbody fusion	surghx26	Repair nerve laceration

Table 3.1 – *Continued*

surghx8	Posterior lateral fusion	surghx27	Repair tendon tear
surghx9	360 (anterior/posterior) fusion	surghx28	Repair ligament tear
Table 3.1 – *Continued*	epair	surghx29	DJD: unspecified procedure
surghx11	Hardware removal	surghx30	DJD: arthroscopic joint decompression or chondroplasty, unspecified
surghx12	Bone stimulator removal	surghx31	soft tissue procedure, unspecified
surghx13	Discectomy + fusion	surghx32	DJD: open arthroplasty
surghx14	Decompression + fusion	surghx33	Joint replacement
surghx15	Neural decompression, spinal (foraminal/central)	surghx34	Joint denervation (ex-facet rhizotomy)
surghx16	Neural decompression, carpal tunnel	surghx35	Neurostimulator
surghx17	Neural decompression, cubital tunnel	surghx36	Medication Pump
surghx18	Neural decompression, thoracic outlet or brachial plexus	sghxot1	# of additional surgeries related to condition
surghx19	Neural decompression, sympathectomy	sghxot2	# of additional surgeries not related to condition

Table 3.2 25 Types of Patients' Physical Histories

Variables	Description
phydx1	Facial 784.0
phydx2	TMJ 524.62
phydx3	Headache 784.0
phydx4	Cervical723.1
phydx5	Thoracic724.1
phydx6	Lumbar724.2
phydx7	Myofascial-Fibromyalgia 729.1
phydx8	Abdominal789.0
phydx9	Pelvic (Female) 625.9
phydx10	Pelvic (Male) 789.0
phydx11	Upper Extremity 729.5
phydx12	Low Extremity 729.5
phydx13	Cancer
phydx14	Osteoarthritis716.9

Table 3.2 – *Continued*

phydx15	Sacro-illitis 724.6
phydx16	Reflex Sympathetic Dystrophy, Unspecified 337.20
phydx17	Reflex Sympathetic Dystrophy, of the Upper Limb 337.21
phydx18	Reflex Sympathetic Dystrophy, of the Lower Limb 337.22
phydx19	Reflex Sympathetic Dystrophy, of Other specified Site 337.29
phydx20	Neuralgia, Neuritis, Unspecified
phydx21	Trigeminal Neuralgia 350.1
phydx22	Atypical Face Pain 350.2
phydx23	Phantom Limb Syndrome 353.6
phydx24	Herpes Zoster with Unspecified Nervous System Complication 053.10
phydx25	Polyneuropathy in Diabetes 357.2
phydxoth	Number of additional physical diagnoses

Table 3.3 26 Types of Patient History of Treatment

Variables	Description
Pastdx1	Facial 784.0
Pastdx2	TMJ 524.62
Pastdx3	Headache 784.0
Pastdx4	Cervical 723.1
Pastdx5	Thoracic 724.1
Pastdx6	Lumbar 724.2
Pastdx7	Myofascial-Fibromyalgia 729.1
Pastdx8	Abdominal 789.0
Pastdx9	Pelvic (Female) 625.9
Pastdx10	Pelvic (Male) 789.0
Pastdx11	Upper Extremity 729.5
Pastdx12	Low Extremity 729.5
Pastdx13	Cancer
Pastdx14	Osteoarthritis 716.9
Pastdx15	Sacro-illitis 724.6
Pastdx16	Reflex SymPathetic Dystrophy, Unspecified 337.20
Pastdx17	Reflex SymPathetic Dystrophy, of the Upper Limb 337.21
Pastdx18	Reflex SymPathetic Dystrophy, of the Lower Limb 337.22
Pastdx19	Reflex SymPathetic Dystrophy, of Other specified Site 337.29

Table 3.3 – *Continued*

Pastdx20	Neuralgia, Neuritis, Unspecified
Pastdx21	Trigeminal Neuralgia 350.1
Pastdx22	Atypical Face Pain 350.2
Pastdx23	Phantom Limb Syndrome 353.6
Pastdx24	Herpes Zoster with Unspecified Nervous System Complication 053.10
Pastdx25	PolyneuroPathy in Diabetes 357.2
Pastdxot	Number of Additional Diagnoses

Table 3.4 13 Other Variables

Variables	Description
duration	Duration
status	Status
marital	Marital
paintype	Paintype
age	Age
onset	Onset
txassign	Txassign
litigat	Litigat
ptsessio	Number of PT Sessions
psysess	Number of Psychologist Sessions
psyout	Psychology Out
physess	Number of physician sessions
othertx	Other treatment modality
vocstat	Vocational Status: Intake
vocmod1	Vocational Status Intake: Recode into 3 groups
sec.gain	Secondary gain issues
secgain2	Secondary gain issues
pschostr	Psychosocial stressors
visithc	Number of healthcare visits in last 6 months
visiter	Number of ER visits in the last 6 months
grp.pre	Group/Pre-treatment score

3.1.2. Variables for treatment options

There are 42 treatment options for pain in this research, including 21 pharmaceutical treatments and 21 procedurals. The variables listed in the previous sub-section are only those from the pre-evaluation point. However, the 42 treatment options occur in all three evaluation points, pre-evaluation, mid-evaluation and post-evaluation point. The treatment variables are listed in the Tables 3.5 and 3.6 (Column 1 is the field name in the database. Column 2 is the description in the database):

Table 3.5 21 Types of Pharmaceutical Treatment

Variables	Description	Variables	Description
dosran1	Tramadol	dosran12	Neuroleptic
dosran2	NSAIDs	dosran13	5HT Agonist
dosran3	Schedule III Narcotic	dosran14	Topical Cream
dosran4	Schedule II Narcotic	dosran15	Benzodiazepine
dosran5	Muscle Relaxant	dosran16	Non Benzodiazepine Anxiolytic
dosran6	Antidepressant-Tricyclic	dosran17	Non Benzodiazepine Sedative
dosran7	Antidepressant-SRI	dosran18	Beta Blocker
dosran8	Antidepressant-NE	dosran19	Alpha Adrenergic Agonist
dosran9	Antidepressant-Multireceptor	dosran20	Calcium Channel Blocker
dosran10	Lithium	dosran21	Other
dosran11	Anticonvulsant		

Table 3.6 21 Types of Procedural Treatment

Variables	Description	Variables	Description
proced1	Trigger Point Injections	proced12	Muscle Stimulator
proced2	Lumbar Epidural Steroid Injections	proced13	Acupuncture
proced3	Cervical Epidural Joint Injection	proced14	Chiropractic
proced4	Facet Joint Injection	proced15	Splints
proced5	Major Joint Injection	proced16	Braces
proced6	Stellate Ganglion Block	proced17	Traction
proced7	Bier's Block	proced18	Psychotherapy
proced8	Ilroinguinal Nerve Block	proced19	Physical Therapy

Table 3.6 – *Continued*

proced9	Somatic Nerve Block	proced20	Bedrest
proced10	Spinal Cord Implant	proced21	PENS
proced11	TENS		

3.1.3 Other Variables Observed Only at Mid-evaluation and Post-evaluation

Table 3.7 shows the variables that are only found in the mid-evaluation point. These variables are used as state variables in the stage 1 of the SDP. Table 3.8 shows the variables that are only found in the post-evaluation point. They are used as state variables in the stage 2 of the SDP. However, most of them had to be eliminated because they had too many missing values that could not be successfully imputed, with the exception of variables numpsyc2 and 3, num.grp2 and 3, num.pt2 and 3.

Table 3.7 Variables at Mid-evaluation

Variables	Description	Variables	Description
aerobic2	Aerobic Exercise Scale - physical therapy	mpmq1	PMQ Question #1
romscal2	ROM scale	mpmq2	PMQ Question #2
strngth2	Strength Scale	mpmq3	PMQ Question #3
adlscal2	ADL Scale	mpmq4	PMQ Question #4
fear2	Fear of Exercise Scale	mpmq5	PMQ Question #5
numpsyc2	number of psychological sessions	mpmq6	PMQ Question #6
num.grp2	Number of group sessions	mpmq7	PMQ Question #7
num.pt2	Number of physical therapy sessions	mpmq8	PMQ Question #8
family	Family Group	mpmq9	PMQ Question #9
opioid1	Type of Opioid1	mpmq10	PMQ Question #10
dose1	Daily Mg Dose 1	mpmq11	PMQ Question #11
opioid2	Type of Opioid2	mpmq12	PMQ Question #12
dose2	Daily Mg Dose 2	mpmq13	PMQ Question #13
morphunt	Total Morphine Units	mpmq14	PMQ Question #14
mpra1	Phys Risk Assess #1	mpmq15	PMQ Question #15
mpra2	Phys Risk Assess #2	mpmq16	PMQ Question #16
mpra3	Phys Risk Assess #3	mpmq17	PMQ Question #17
mpra4	Phys Risk Assess #4	mpmq18	PMQ Question #18
mpra5	Phys Risk Assess #5	mpmq19	PMQ Question #19

Table 3.7 – *Continued*

mpra6	Phys Risk Assess #6	mpmq20	PMQ Question #20
mpratot	Phys Risk Assess Total	mpmq21	PMQ Question #21
earlyrx	Made Any Early Rx Refill Requests	mpmq22	PMQ Question #22
numearly	Number of Early Rx Refill Requests	mpmq23	PMQ Question #23
rxdeny	Any Early Rx Refill Requests Denied	mpmq24	PMQ Question #24
mpmq26	PMQ Question #26	mpmq25	PMQ Question #25

Table 3.8 Variables at Post-evaluation

Database Name	Description
vocaton3	Vocational Status - Discharge
vocmod3	Vocational Status - Discharge: Recode into 3 groups
secgain3	Secondary gain issues
secgn3.2	Secondary gain issues
numpsyh3	Number of psychological sessions
num.pt.3	Number of PT sessions
md2.in	Number of physician sessions within clinic
md2.out	Number physician visit outside of clinic
num.grp3	Number of group sessions
grp.post	Group/Post treatment score
ottx.3	Number of Sessions of other treatment modality
tx.compl	Completed treatment as prescribed

3.1.4 Observation Counts of Variables

The following three tables show the counts of variables at three evaluation points as below. As we can see, there are many variables having zero counts. Therefore, the next step is to group some variables based on their similarities.

Table 3.9 Counts for Pre-evaluation Variables

proc1.1	12	dsran1.1	21	surghx1	11	surghx23	0	phydx1	3	pastdx1	1
proc1.2	20	dsran1.2	60	surghx2	0	surghx24	0	phydx2	1	pastdx2	1
proc1.3	6	dsran1.3	35	surghx3	0	surghx25	0	phydx3	12	pastdx3	9
proc1.4	11	dsran1.4	12	surghx4	0	surghx26	0	phydx4	33	pastdx4	20

Table 3.9 – *Continued*

proc1.5	6	dsran1.5	37	surghx5	10	surghx27	0	phydx5	10	pastdx5	8
proc1.6	1	dsran1.6	21	surghx6	2	surghx28	0	phydx6	53	pastdx6	26
proc1.7	1	dsran1.7	21	surghx7	0	surghx29	1	phydx7	24	pastdx7	21
proc1.8	0	dsran1.8	1	surghx8	1	surghx30	0	phydx8	6	pastdx8	3
proc1.9	2	dsran1.9	5	surghx9	0	surghx31	0	phydx9	1	pastdx9	1
proc1.10	0	dsra1.10	0	surghx10	0	surghx32	1	phydx10	2	pastdx10	2
proc1.11	22	dsra1.11	18	surghx11	0	surghx33	0	phydx11	17	pastdx11	17
proc1.12	3	dsra1.12	0	surghx12	0	surghx34	0	phydx12	25	pastdx12	19
proc1.13	12	dsra1.13	1	surghx13	0	surghx35	0	phydx13	0	pastdx13	0
proc1.14	15	dsra1.14	0	surghx14	3	surghx36	0	phydx14	8	pastdx14	10
proc1.15	2	dsra1.15	18	surghx15	6	sghxot1	16	phydx15	2	pastdx15	1
proc1.16	3	dsra1.16	1	surghx16	2	sghxot2	13	phydx16	0	pastdx16	0
proc1.17	1	dsra1.17	2	surghx17	0			phydx17	1	pastdx17	1
proc1.18	5	dsra1.18	2	surghx18	0			phydx18	1	pastdx18	0
proc1.19	45	dsra1.19	0	surghx19	0			phydx19	0	pastdx19	0
proc1.20	12	dsra1.20	1	surghx20	0			phydx20	3	pastdx20	1
proc1.21	0	dsra1.21	5	surghx21	0			phydx21	0	pastdx21	0
proc1.22	18			surghx22	0			phydx22	0	pastdx22	0
								phydx23	0	pastdx23	0
								phydx24	0	pastdx24	0
								phydx25	0	pastdx25	1
								phydxoth	16	pastdxot	6

Table 3.10 Counts at Mid-evaluation

proc2.1	6	dsran2.1	26	numpsyc2	104
proc2.2	10	dsran2.2	53	num.grp2	67
proc2.3	5	dsran2.3	24	num.pt2	77
proc2.4	2	dsran2.4	14	aerobic2	69
proc2.5	6	dsran2.5	41	romscal2	68
proc2.6	1	dsran2.6	28	strngth2	68
proc2.7	0	dsran2.7	23	adlscal2	69
proc2.8	0	dsran2.8	5	fear2	68
proc2.9	0	dsran2.9	15		

Table 3.10 – *Continued*

proc2.10	0	dsra2.10	0
proc2.11	6	dsra2.11	12
proc2.12	2	dsra2.12	0
proc2.13	0	dsra2.13	0
proc2.14	0	dsra2.14	0
proc2.15	0	dsra2.15	14
proc2.16	0	dsra2.16	0
proc2.17	0	dsra2.17	2
proc2.18	83	dsra2.18	0
proc2.19	76	dsra2.19	0
proc2.20	2	dsra2.20	0
proc2.21	6	dsra2.21	6
proc2.22	8		

Table 3.11 Counts at Post-evaluation

proc3.1	7	dsran3.1	27	numpsyc3	115
proc3.2	10	dsran3.2	43	num.grp3	65
proc3.3	3	dsran3.3	21	num.pt3	65
proc3.4	2	dsran3.4	7	vocaton3	105
proc3.5	3	dsran3.5	39	vocmod3	105
proc3.6	0	dsran3.6	34	secgain3	20
proc3.7	0	dsran3.7	21	secgn3.2	2
proc3.8	1	dsran3.8	1	md.in	88
proc3.9	0	dsran3.9	12	md.out	36
proc3.10	1	dsra3.10	0	ottx.3	3
proc3.11	12	dsra3.11	19	tx.compl	97
proc3.12	3	dsra3.12	0		
proc3.13	0	dsra3.13	0		
proc3.14	1	dsra3.14	1		
proc3.15	0	dsra3.15	18		
proc3.16	0	dsra3.16	1		
proc3.17	1	dsra3.17	0		
proc3.18	56	dsra3.18	0		

Table 3.11 – *Continued*

proc3.19	49	dsra3.19	0
proc3.20	0	dsra3.20	0
proc3.21	4	dsra3.21	3
proc3.ot	13		

3.1.5 Grouping Variables of Patients' Background

Since it can be seen that there are many empty cells in the above treatment counts, indicating treatments that were never applied, a statistical analysis cannot include these zero-count treatments. To overcome this without eliminating treatment options, surgical history, physical history, past diagnostic and the treatments are grouped, so as to eliminate zero counts (per group). The following tables show how the variables are grouped. A statistical analysis will then employ these group variables.

As we can see in the following three tables, the variables of surgical history are reduced from 36 to 4. Then, physical history variables are reduced from 25 to 9, but here we did not group any variables and only eliminate the ones with the counts smaller than 4, the same as past diagnosis. The variables of past diagnosis are decreased from 25 to 8.

Table 3.12 Grouping Variables of Surgical History

Variables	Description	Group	Counts	Total
surghx1	Unspecified discectomy		11	
surghx2	Microdiscectomy	**SghxGr1**	0	11
surghx3	Percutaneous discectomy		0	
surghx4	Chemonucleolysis		0	
surghx5	Unspecified fusion		10	
surghx6	Anterior fusion		2	
surghx7	Posterior interbody fusion	**SghxGr2**	0	13
surghx8	Posterior lateral fusion		1	
surghx9	360 (anterior/posterior) fusion		0	
surghx10	Pseudoarthrosis repair		0	
surghx11	Hardware removal		0	
surghx12	Bone stimulator removal		0	

Table 3.12 – *Continued*

surghx13	Discectomy + fusion		0	
surghx14	Decompression + fusion	**SghxGr3**	3	3
surghx15	Neural decompression, spinal (foraminal/central)		6	
surghx16	Neural decompression, carpal tunnel		2	
surghx17	Neural decompression, cubital tunnel		0	
surghx18	Neural decompression, thoracic outlet or brachial plexus	SghxGr4	0	8
surghx19	Neural decompression, sympathectomy		0	
surghx20	Neural decompression, other		0	
surghx21	Fracture-dislocation: closed reduction		0	
surghx22	Fracture-dislocation, open reduction		0	
surghx23	Pseudoarthrosis repair (same with surghx10)		0	
surghx24	Hardware Removal		0	
surghx25	Amputation		0	
surghx26	Repair nerve laceration		0	
surghx27	Repair tendon tear		0	
surghx28	Repair ligament tear		0	
surghx29	DJD: unspecified procedure		1	
surghx30	DJD: arthroscopic joint decompression or chondroplasty, unspecified		0	1
surghx31	Soft tissue procedure, unspecified		0	
surghx32	DJD: open arthroplasty		1	
surghx33	Joint replacement		0	
surghx34	Joint denervation (ex-facet rhizotomy)		0	
surghx35	Neurostimulator		0	
surghx36	Medication Pump		0	

3.1.6 Grouping Variables of Treatments

From Table 3.15, we can see the number of variables is reduced from 21 to 8 after grouping. We put Dsran_3 and 4 to RxGr3 because they are all narcotic. Drsran_6, 7, 8 and 9 are grouped together as RxGr5 since they are all antidepressant. Drsran_10, 11, 12, 13 are all together as group of RxGr6 since they are different kinds of tranquilizers. Drsran_15, 16, 17 are

in the group of RxGr7 because they are all sleeping pills. We put Drsran_14, 18, 19, 20, 21 into the group of others, RxGr8.

Moreover, in Table 3.16, the variables for procedures are reduced from 22 to 11 after grouped. The first group, ProcGr1, has variables of proced_1, 2, 3, 4, 5 because they are all about injection. ProcGr2 has proced_6, 7, 8, 9 because they are all related on pain block. In the fourth group, ProcGr4, we put procede_11, 12, 21 together because they are all about stimulation. In ProcGr7, it has procede_15, 16, 20 because they are auxiliaries. It should be noted here that procede_20 and 21 are not in the number order as grouped.

Table 3.13 Grouping Variables of Pharmaceutical Treatments

Mid-point	Description	# of Count	Total Counts	Group
dsran_1	Tramadol	22	22	**RxGr1**
dsran_2	NSAIDs	53	53	**RxGr2**
dsran_3	Schedule III Narcotic	22	36	**RxGr3**
dsran_4	Schedule II Narcotic	14		Narcotic
dsran_5	Muscle Relaxant	39	39	**RxGr4**
dsran_6	Antidepressant-Tricyclic	27	69	**RxGr5**
dsran_7	Antidepressant-SRI	23		Antidepressant
dsran_8	Antidepressant-NE	4		
dsran_9	Antidepressant-Multireceptor	15		
dsran_10	Lithium	0	12	**RxGr6**
dsran_11	Anticonvulsant	12		Tranquilizer
dsran_12	Neuroleptic	0		
dsran_13	5HT Agonist	0		
dsran_15	Benzodiazepine	14	16	**RxGr7**
dsran_16	Non Benzodiazepine Anxiolytic	0		Sleeping Pills
dsran_17	Non Benzodiazepine Sedative	2		
dsran_14	Topical Cream	0	6	**RxGr8**
dsran_18	Beta Blocker	0		Others
dsran_19	Alpha Adrenergic Agonist	0		
dsran_20	Calcium Channel Blocker	0		

Table 3.13 – *Continued*

dsran_21	Others	6		

* NSAIDs (Non-steroidal anti-inflammatory drugs)

Table 3.14 Grouping Variables of Procedural Treatments

Variables	Description	# of Count	Total Counts	Group
Proced_1	Procedures for pain/Trigger Point Injections	6	29	**ProcGr1** Injection
proced_2	Procedures for pain/Lumbar Epidural Steroid Injections	10		
proced_3	Procedures for pain/Cervical Epidural Joint Injection	5		
proced_4	Procedures for pain/Facet Joint Injection	2		
proced_5	Procedures for pain/Major Joint Injection	6		
proced_6	Procedures for pain/Stellate Ganglion Block	1	1	**ProcGr2** Block Procedure
proced_7	Procedures for pain/Bier's Block	0		
proced_8	Procedures for pain/Ilroinguinal Nerve Block	0		
proced_9	Procedures for pain/Somatic Nerve Block	0		
proced_10	Procedures for pain/Spinal Cord Implant	0	0	**ProcGr3**
proced_11	Procedures for pain/ TENS (Transcutaneous Electrical Nerve Stimulation)	6	14	**ProcGr4** Stimulation Procedure
proced_12	Procedures for pain/Muscle Stimulator	2		
proced_21	PENS (Percutaneous Electrical Nerve Stimulation)	6		
proced_13	Acupuncture	0	0	**ProcGr5**
proced_14	Chiropractic	0	0	**ProcGr6**
proced_15	Splints	0	2	**ProcGr7** Auxiliaries
proced_16	Braces	0		
proced_20	Bedrest	2		
proced_17	Traction	0	0	**ProcGr8**
proced_18	Psychotherapy	83	83	**ProcGr9**
proced_19	Physical Therapy	76	76	**ProcGr10**
proced_22	Number of Additional Procedures	8	8	**ProcGr11**

3.1.7 Stages, State Variables, and Decision Variables

This research employs the data provided from Robbins et al. (2003). State variables are the variables storing patients' health parameters. In this case, they are patients' personal

information, surgical history (surghx), review of the medical record (pastdx), physical examination (phydx) and 42 prior treatments (treatments at pre-evaluation). Patients' personal information includes gender, age, marital status, the numbers of children and pending litigation related to pain. Decision variables are patients' treatment options at each stage. In other words, there are 42 decision variables in each stage. This application has two stages, where stage 1 begins at the pre-evaluation point, and stage 2 begins at the mid-evaluation point.

3.1.8 Re–Specify Variables

After eliminating observations with missing dataset, imputing possible values and grouping similar treatments, in the final cleaned dataset, we have 89 observations comparing with 70 variables, containing 35 variables of patients' information, 6 variables of mid-evaluation, 3 variables of post-evaluation and 13 treatment variables for each stage (8 groups of dosage treatments, 5 groups of procedure treatments). Table 3.15 lists and re-specifies all the variables in the way used in our models. In the treatment variables and mid-evaluation variables, the subscript numbers represent the stage of that variable. The specification of stage can be found in Figure 1.1. For more information of other variables in the raw dataset, please refer to previous subsections.

Table 3.15 Variables in the cleaned dataset

Variables	Description from Database of Robbins et al. (2003)
Duration	Duration
Status	Status
OnSet	OnSet
PainType	Pain Type
TxAssign	TxAssign
Age	Age
Marital	Marital
Children	Children
Litigat	Litigat
SghxGr1	Surgical history group 1 (Discectomy)
SghxGr2	Surgical history group 2 (Fusion)
SghxGr4	Surgical history group 4 (Neural decompression)

Table 3.15 – *Continued*

Sghxot1	# of additional surgeries related to condition
Sghxot2	# of additional NOT surgeries related to condition
PhyDx3	Physical histories of Headache 784.0
PhyDx4	Physical histories of Cervical723.1
PhyDx5	Physical histories of Thoracic724.1
PhyDx6	Physical histories of Lumbar724.2
PhyDx7	Physical histories of Myofascial-Fibromyalgia 729.1
PhyDx8	Physical histories of Abdominal789.0
PhyDx9	Physical histories of Pelvic (Female) 625.9
PhyDx11	Physical histories of Osteoarthritis716.9
PhyDx14	Physical histories of Upper Extremity 729.5
PhyDxoth	Number of additional physical diagnoses
PastDx3	Past diagnoses of Headache 784.0
PastDx4	Past diagnoses of Cervical723.1
PastDx5	Past diagnoses of Thoracic724.1
PastDx6	Past diagnoses of Lumbar724.2
PastDx7	Past diagnoses of Myofascial-Fibromyalgia 729.1
PastDx11	Past diagnoses of Abdominal789.0
PastDx14	Past diagnoses of Pelvic (Female) 625.9
PastDxot	Number of additional diagnoses
PreBDI	BDI in the pre-evaluation point
PreOSW	OSW in the pre-evaluation point
PrePDA	PDA in the pre-evaluation point
$RxGr1_1$	Medication group 1 (Tramadol) in stage 1
$RxGr2_1$	Medication group 2 (NSAID) in stage 1
$RxGr3_1$	Medication group 3 (Narcotic) in stage 1
$RxGr4_1$	Medication group 4 (Muscle Relaxant in stage 1
$RxGr5_1$	Medication group 5 (Antidepressant) in stage 1
$RxGr6_1$	Medication group 6 (Tranquilizer) in stage 1
$RxGr7_1$	Medication group 7 (Sleeping Pill) in stage 1
$RxGr8_1$	Medication group 8 (Other) in stage 1
$ProcGr1_1$	Injection procedure in stage 1
$ProcGr4_1$	Stimulation procedure in stage 1
$ProcGr9_1$	Psychotherapy in stage 1
$ProcGr10_1$	Physical therapy in stage 1
$ProcGr11_1$	Number of additional procedures in stage 1
MidBDI	BDI at the mid-evaluation point
MidOSW	OSW at the mid-evaluation point

Table 3.15 – *Continued*

MidPDA	PDA at the mid-evaluation point
$NumPsy_1$	Number of psychological sessions
$NumGr_1$	Number of group sessions
$NumPT_1$	Number of physical therapy sessions
$RxGr1_2$	Medication group 1 (Tramadol) in stage 2
$RxGr2_2$	Medication group 2 (NSAID) in stage 2
$RxGr3_2$	Medication group 3 (Narcotic) in stage 2
$RxGr4_2$	Medication group 4 (Muscle Relaxant in stage 2
$RxGr5_2$	Medication group 5 (Antidepressant) in stage 2
$RxGr6_2$	Medication group 6 (Tranquilizer) in stage 2
$RxGr7_2$	Medication group 7 (Sleeping Pill) in stage 2
$RxGr8_2$	Medication group 8 (Other) in stage 2
$ProcGr1_2$	Injection procedure in stage 2
$ProcGr4_2$	Stimulation procedure in stage 2
$ProcGr9_2$	Psychotherapy in stage 2
$ProcGr10_2$	Physical therapy in stage 2
$ProcGr11_2$	Number of additional procedures in stage 2
PostBDI	BDI the post-evaluation point
PostOSW	OSW at the post-evaluation point
PostPDA	PDA at the post-evaluation point

3.1.9 Outcome Measurements

In the raw data, there are 18 different outcome measures: Beck Depression Inventory (BDI), Dallas Pain Questionnaire (dpq), Medical Outcomes Short Form-36 Health-Status Survey (sf36), Oswestry Pain Disability Questionnaire (OSW), Pain Drawing Analogue (PDA), Multidimensional Pain Inventory (mpi), and twelve different Treatment Helpfulness Questionnaire metrics (thq1 to thq12). As will be described in section 3.1, the prototype focuses on three of them – OSW (Oswestry), PDA (Pain Drawing Analogue), and BDI (BDI total score).

The Beck Depression Inventory (BDI) is a self-reported measure of depression. A total score of 0-10 is considered normal; 11-14 mild depression; 15-18 moderate depression; 19-30 severe depression; and >30 very severe depression. Dallas Pain Questionnaire (dpq) is a 15 item analog, self-reported scale measuring perceived pain and disability. The scores from 0 to

39 represent mildly disabling pain, the scores from 40 to 84 represent moderately disabling pain, the scores larger and equal to 85 represent severely disabling pain (Robbins et al. 2003).

The Medical Outcomes Short Form -36 Health-Status Survey (sf36) is a self-reported measure of mental and physical function with a mean normal score = 50; higher scores reflect better functioning. The Oswestry Pain Disability Questionnaire (OSW) is used to measure perceived functional disabilities caused by pain. For a total score of 0-10 no treatment is necessary; 11-20 conservative treatments are recommended; 21-30 detail investigations are recommended; 31-40 severe intervention is recommended; and for 41-50 the patient should be bed bound (European Medical Tourist 2010). The Pain Drawing Analogue (PDA) asks that patients mark their level of pain along a 10-cm visual analog scale (1 to 10) (Robbins et al. 2003).

The Multidimensional Pain Inventory (mpi) yields three coping styles – adaptive, dysfucntional, interpersonally distressed – and also has three nonprotypical profiles –hybrid, anomalous, unalayzable (1: adaptive cooper, 2: interpersonally distressed, 3: dysfunctional, 4: missing data, 5. anomalous). The Treatment Helpfulness Questionnaire (thq) is used to measure patient's satisfaction with their assessment-treatment care; it has 12 different kinds – thq1: program, thq2: medical assessment & treatment, thq3: psych. assessment & treatment, thq4: pt assessment & treatment, thq5: office visits with physician, thq6: individual psych therapy, thq7: medical diagnositc tests, thq8: medical work, thq9: patient education groups, thq10: group counseling, thq11: epidural steroid injections, and thq12: medication alone (Robbins et al. 2003).

In order to separately represent outcome measures at each evaluation point, we denote them with “pre, mid, and post” corresponding to the program evaluation points. For instance, if there is an outcome variable called Pre_OSW, it represents the outcome measure of Oswestry Pain Disability Questionnaire at pre-evaluation point. Therefore, at the pre-evaluation point, the variables of outcome measures are Pre_BDI, Pre_dpq, Pre_sf36, Pre_OSW, Pre_PDA,

Pre_mpi, and Pre_thq1 to Pre_thq12; at the mid-evaluation point, the variables of outcome measures are Mid_BDI, Mid_dpq, Mid_sf36, Mid_OSW, Mid_PDA, Mid_mpi, and Mid_thq1 to Mid_thq12; at the post-evaluation point, the variables of outcome measures are Post_BDI, Post_dpq, Post_sf36, Post_OSW, Post_PDA, Post_mpi, and Post_thq1 to Post_thq12.

3.1.10 Data Issues

The database contained many missing and invalid values. If all observations with missing or invalid data were eliminated, then the number of observations would be reduced to only 60. Hence, when possible, a regression approach was applied to impute missing values. This enabled us to keep 89 observations. However, this is still not sufficient to explore all the treatment options and state variables.

More importantly, many treatment options were not applied or were applied rarely. Therefore, they were grouped based on their similarities. As shown in section 3.1, the 21 pharmaceutical treatments were combined into 8 categories (Tramadol, NSAIDs, narcotic, muscle relaxant, antidepressant, tranquilizer, sleeping pills and others), and the 21 procedural treatments were combined into 11 categories (injection procedures, block procedures, spinal cord implant, stimulation procedures, acupuncture, chiropractic, auxiliaries, traction, psychotherapy, physical therapy, number of additional procedures). Even following this, 6 procedure groups (block procedures, spinal cord implant, acupuncture, chiropractic, auxiliaries, traction) were eliminated due to an insufficient count.

Finally, it should be noted that the data set contained a mix of categorical and numerical variables, where the categorical variables were primarily binary (e.g., Procedure = 1 if applied, and 0 if not), although some had more categories (e.g. pain type, pain status). A Tree-MARS had been applied previously to properly address this mix of variable types (Sahu et al. 2009); however, it was found that the regression model yielded better predictions. Proper handling of a mix of categorical and continuous state variables in SDP is an area of future research.

3.2 Building Models

3.2.1. DP Framework for Pain Management

Our primary objective is to minimize BDI, OSW, and PDA as the patient moves through the two-stage system. The decision variables are the possible treatment plans, which can be combinations of 21 types of pharmaceuticals, such as NSAIDs (Non-steroidal anti-inflammatory drugs), narcotics, muscle relaxants, antidepressants, tranquilizers, sleeping pills, and 21 types of medical procedures, such as injections, nerve blocks, acupuncture, braces, psychotherapy. The state of the system is specified at the beginning of each stage. At the beginning of Stage 1, the state variables consist of all variables collected by the pre-treatment evaluation, which includes the three pain outcome measures and medical history relevant to pain. This specifies all aspects of a patient's pain status immediately prior to beginning treatment and this first stage decision is based on this state. At the beginning of Stage 2, the three pain outcome measures are observed again, and the state variables consist of these new observations, the decision variables specifying the Stage 1 treatment plan, and all the state variables from Stage 1 and the mid-evaluation. For the DP formulation, we need models for how the state of the system transitions from Stage 1 to Stage 2 and additionally for predicting BDI, OSW, and PDA at the post-evaluation point. Our approximate DP process will additionally conduct the dimension reduction process described in Yang et al. (2007) to reduce the set of state variables to only those that are necessary to maintain for the modeling of state transitions and outcome measures. Finally, once solved, the future value functions in each stage will provide the critical information for specifying the optimal policy.

3.2.2 DP Formulation of Pain Management

While a major task in the larger pain management project is solving the DP problem, this research focuses on the process for approximating the unknown relationships that represent the state transition functions and that predict pain outcomes. Our approximate DP

process is similar to that of Yang et al. (2009). Since we employ a backward solution approach, we specify the optimization formulations below, starting with the last stage, Stage 2.

For Stage 2:

$$\text{Future Value Function Objective: } V_2(x_2) = \min_{u_2} E\{c_2(x_2, u_2, \varepsilon_2)\}$$

$$Contraints: u_2 \in \Gamma_2$$

x_2 is the vector of pre/mid *health parameters* and prior treatment,

u_2 is a vector representing the modified *treatment plan*,

ε_2 is a vector of *random* variables,

$c_2(\cdot)$ is a function of treatment and mid-outcome penalty costs,

Γ_2 is the set of *constraints.*

For Stage 1:

$$\text{Future Value Function Objective: } \tilde{V}_1(x_1) = \min_{u_1} E\{c_1(x_1, u_1, \varepsilon_1) + \hat{V}_2(\hat{x}_2)\}$$

$$\text{State Transition: } s.t.\ \hat{x}_2 = f_1(x_1, u_1, \varepsilon_1)$$

$$\text{Contraints: } u_1 \in \Gamma_1$$

x_1 is the vector of pre-evaluation *health parameters*,

u_1 is a vector representing the initial *treatment plan*,

ε_1 is a vector of *random* variables,

$c_1(\cdot)$ is a function of treatment and post-outcome penalty costs,

$f_1(\cdot)$ is the state transition function from Stage 1 to 2,

Γ_1 is the set of *constraints.*

The state variables $\boldsymbol{x}_i$ contain the background and health parameters of patients, e.g., age, gender, surgical and physical histories, past diagnoses, and prior treatments (which for Stage 2 includes the initial treatment plan). The decision variables $\boldsymbol{u}_i$ represent treatment options, dosage for pharmaceuticals, and procedural treatments. Uncertainty in the system is represented by the random variable $\boldsymbol{\varepsilon}$. The cost function in Stage 1, $C_1(\cdot)$, contains an

increasing utility cost on the initial treatment plan and a penalty cost for mid-evaluation pain outcomes above the "normal" level. Similarly, the cost function in Stage 2, $C_2(\cdot)$, contains an increasing utility cost on the modified treatment plan and a penalty cost for post-evaluation pain outcomes above the "normal" level. The state transition from Stage 1 to 2 is represented by $f_1(\cdot)$, and constraint sets are represented by Γ_1 and Γ_2. The future value functions provide the minimum expected cost of treatment and the penalty on the pain outcomes, subject to the constraints on the decision variables. The future value function of Stage 2, $V_2(\cdot)$, is needed to solve for the future value function of Stage 1. Given the continuous or near-continuous nature of several state variables, we cannot solve exactly for $V_2(\cdot)$. Hence, we will need an approximation $\hat{V}_2(\cdot)$ and this is what is shown in the objective for Stage 1.

3.2.3. Objective Function

A penalty strategy is used in our objective function for the future value function (Yang 2004). Hence, our objective function is comprised of two parts, treatment cost and outcome penalty cost functions. The general forms of these cost functions are discussed in sections 3.2.4 and 3.2.5. The purpose of the treatment cost function is to place higher cost on higher treatment, and the purpose of the penalty function it is to achieve acceptable outcome measures of pain. For the optimization, it is necessary to balance the treatment and pain penalty costs at each stage. Additional coefficients are calibrated to achieve this. In this dissertation, two coefficients are applied, α and β. With these two coefficients, we can adjust the balance of the two cost functions so that one does not dominate the other. Five beta values are applied in this dissertation, depending on the ranges of pharmaceutical treatment; the final alpha values are 0.0025 for the penalty cost functions of BDI and OSW and 0.003 for the penalty cost function of PDA.

3.2.4. Treatment Utilization Functions for Pain Management

Since different pharmaceutical and procedural treatments have different ranges for specifying usage, different treatment cost functions were formulated by applying different beta

coefficients. This dissertation has five different ranges of pharmaceutical and procedural treatments, corresponding to five beta values (6.13, 1.91, 0.92, 0.54 and 0.36) as shown in Figure 3.2. For instance, if the dosage range is from 0 to 3, the corresponding β is 0.92, the treatment cost is 2 when the dosage level is 1, and the treatment cost becomes 14 when the dosage level is 3. The following equation defines the general form of an individual treatment cost function:

$$TC = \beta \times (4.5 \times (u + 0.1)^2 - 3 \times u^2)$$

TC is the individual treatment cost,

β is the coefficient for the specific treatment cost,

u is the decision variable.

The total treatment cost function for multiple pharmaceutical and/or procedural treatments is the sum for the individual treatment cost functions.

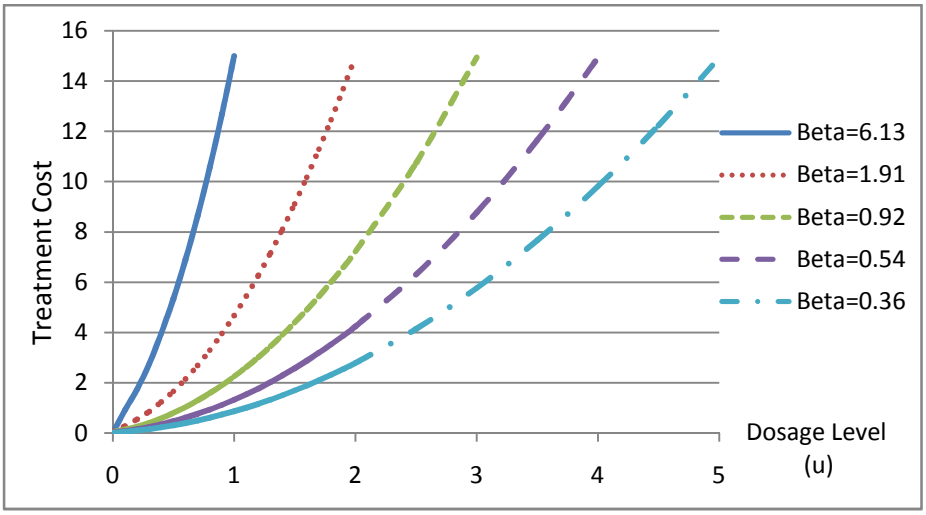


Figure 3.2 Treatment Cost Function

3.2.5 Outcome Penalty Cost Functions for Pain Management

Two different outcome penalty cost functions are employed here because the different ranges of outcome measures. The outcome measures BDI and OSW range from 0 to 50, and the outcome measure PDA ranges from 0 to 10. Figure 3.3 shows the penalty cost function for

outcome measures BDI or OSW. The below equation defines their penalty cost function. The alpha value in this case is 0.0025. As seen in Figure 3.3, we start the penalty begins to rise after BDI passes a level of 11. This is because the outcome measures of BDI and OSW are considered to be in the normal range (or no treatment needed), if they are 10 or lower (see section 3.1.8,

$$PF = \alpha \times \begin{cases} 0\,, & f \le 10 \\ 0.62 \times 10^2 \times (F-9)^2 - 30 \times (F-5)\,, & f \ge 11 \end{cases}$$

PF is the penalty cost,

α is the coefficient for the penalty cost of BDI and OSW,

F is the outcome measure (BDI or OSW).

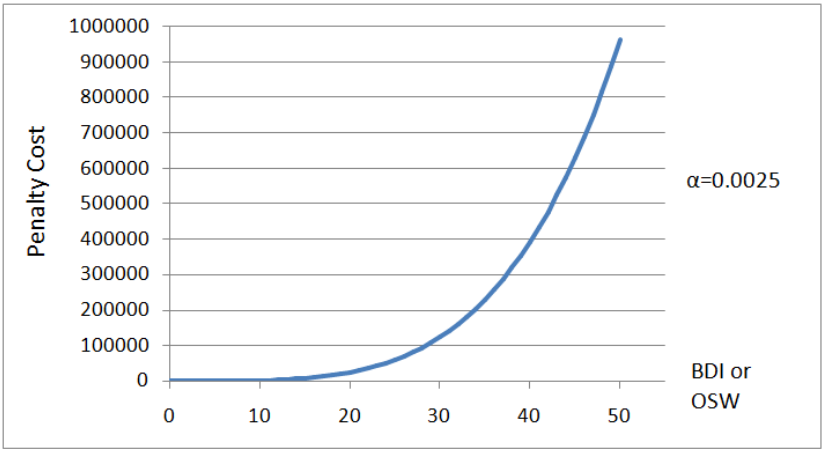


Figure 3.3 Penalty Function for BDI or OSW

The Figure 3.4 shows the penalty cost function for outcome measure of PDA. Its function is defined below. The alpha value of PDA is 0.003. In this case, the penalty starts to rise once PDA is not zero.

$$PF = \alpha \times (8.15 \times 10^2 \times F^2 - 6.25 \times F), \qquad f > 0$$

PF is the penalty cost,

α is the coefficient for penalty cost function of PDA,

F is the outcome measure of PDA.

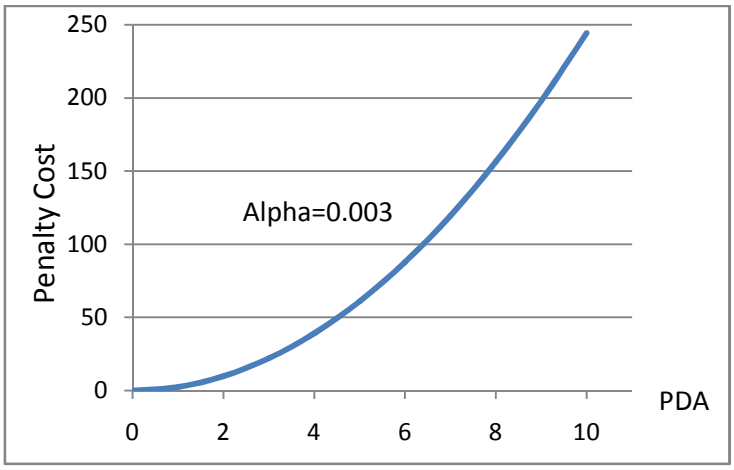


Figure 3.4 Penalty Function for PDA

3.2.6. Optimization Module

The fmincon function in Optimization Toolbox of Matlab conducts constrained nonlinear programming and is employed in the SDP solution algorithm for the adaptive pain management framework (MathWorks 2010). Given initial starting points, it seeks to minimize an objective dependent on several variables subject to constraints. We used it to optimize the decision variables in each stage.

3.2.7. Approximation Module

The approximation of the future value function in stage 2 uses an artificial neural network (ANN) method. We employed the newff function of the Neural Network toolbox in Matlab in toolbox. The ANN structure assumed one hidden layer, and after some trial and error, the number of hidden nodes was set to 20. This structure appeared to work well for all three outcome measures. The selection of number of hidden nodes was based on the comparison of 10, 15, 20, 40 and re-generated another testing dataset to compare. The results show that the 20 hidden nodes yield lower errors (Appendix C). The inputs for the approximation were the stage 2 state variables. The PostBDI model has 13 stage 2 state variables; the PostOSW model has 8; and the PostPDA model has 15. Since the modeling was conducted separately, each ANN model has only one output corresponding to the stage 2 future value function.

CHAPTER 4

IMPLEMENTATIONS AND COMPUTATIONAL RESULTS

For the adaptive pain management SDP, the goal is to minimize treatment cost and outcome measures of pain by using the patient's past and present information. The SDP solution approach in this dissertation uses the algorithm in Figure 2.3 in our approximate DP process shown in Figure 3.1. The discretization points were generated using a Latin hypercube (LH) experimental design with 50 points. For each of the 50 discretization points, a corresponding point on the future value function is obtained by conducting the minimization. Because the pain management SDP involves only two stages, it was only necessary to approximate the stage 2 future value function, which is needed to conduct the stage 1 minimization. Hence, in the last stage (stage 2), the minimization of the cost objective, which consists of treatment and outcome penalty costs, is conducted at each of the 50 discretization points, and then these data were used to construct an ANN model as a continuous approximation of the future value function.

Although the optimal decisions, i.e., the treatment plan, can be ascertained from the backward SDP solution approach, the technique of on-line forward re-optimization has been seen to achieve better accuracy in optimizing the decisions (Tejada-Guibert et al. 1993, Yang 2004, Cervellera and Macciò 2010). In section 4.1, the constructs of outcome and state transition modeling are unraveled using regression analysis in SAS software (SAS. 2010). The approximate of the SDP stage 2 future value function is presented in section 4.2. The simulation of on-line SDP re-optimization is discussed in section 4.3. The algorithm of re-optimization and its comparisons are specified in section 4.4.

The implementations of the backward SDP solution approach and forward re-optimization were coded in Matlab; they were executed on a laptop with a Core 2 Duo

processor at 2.27 GHz and 4 GB memory. On average, it takes about 10 minutes to solve the backward SDP approach and about 3 hours to conduct 1000 simulations of the on-line re-optimization process of all 89 patients, for each of the three outcome measures.

4.1 Constructing SDP Outcome Measures Models and State Transition Functions

After all data issues, described in section 3.1.9, were addressed, the clean dataset of pain management program consisted of 89 patients with 70 variables. An SDP policy was derived separately for each of the three different outcome measures of pain. Future work will address the multi-objective nature of the problem (see Chapter 5). Given the clean dataset, the first task was to estimate how the state variables transition from stage 1 to stage 2. The state transition must include any information needed in stage 2 to predict the post-evaluation pain outcomes, which are incorporated in the stage 2 cost objectives. If a stage 1 state variable is needed in stage 2, then an "identity" transition (Yang 2004) is used to simply pass that information directly from stage 1 to stage 2.

For each outcome measure (BDI, OSW, PDA), linear regression was used to model the outcome predicted at the mid-evaluation point, the state transition from stage 1 to stage 2, and the outcome predicted at the post-evaluation point. The stage 1 state and decision variables were used as predictor variables to construct the mid-evaluation outcome regression model and the state transition from stage 1 to stage 2. Similarly, the stage 2 state and decision variables were used as predictor variables to construct the post-evaluation outcome regression model, State variables are classified as patients' background information, and decision variables are pharmaceutical or procedural treatments. Stepwise regression was employed to identify only the statistically significant predictor variables. Eliminating insignficant predictor variables reduces the dimension of the SDP problem. The selections of important variables are based on their p-values and variance inflation factors (VIF). . Simple regression models were first created for preliminary testing of the SDP code. However, the final models required transformations to satisfy linear regression model assumptions, and (standardized) interaction terms between state

and decision variables to adequately represent the complexity of the relationships (Appendix A). More details on the modeling process is described next.

To identify the best outcome regression model, two preliminary models were explored first to determine if the model assumptions were satisfied. For the BDI models, the post-evaluation OSW model, and the $NumPT_1$ model, a slight funnel shape in the residuals vs. fitted values plot indicated a violation of the constant variance assumption. Hence, the square root transformation was employed for these models to rectify this. Following the validation of the model assumptions, three predictor variable sets involving standard interactions between state and decision variables were explored by stepwise regression. Specifically, predictor variable set A included all 70 variables and interaction terms only between state and decision variables that were selected as significant for the preliminary model; predictor variable set B included all significant variables from the preliminary model and interaction terms based on all decision variables and only the selected state variables from the determined preliminary model; and predictor variable set C included all variables and interaction terms from all decision and state variables. Stepwise regression was applied to each of the predictor variable sets to identify a set of selected variables for each case.

Table 4.1 summaries information of the outcome models and transition functions. As we can see in the table, it shows that the models using predictor variable set C were best for all cases, and the number of variables has been reduced. More details for each outcome measure are addressed in the following sub sections, 4.1.1 BDI models, 4.1.2 OSW models, 4.1.3 PDA models. The details on all the regression models and the assessment of model assumptions are given in Appendix A. The listing of the variable notation can be found in Table 3.15 in Chapter 3. For each outcome measure, the post-evaluation model is developed first. The state variables that are selected as significant variables in the post-evaluation model must be included as stage 2 state variables. State transition models must be developed to realize each of the stage 2 state variables. The transition can be defined as an “identity transition,” if a stage 2 state variable was

realized at the pre-evaluation point. Identity transitions are also used for decision variables that are needed in stage 2, but were realized in stage 1, prior to the mid-evaluation point. All other stage 2 state variables will require additional regression models to be constructed to predict them. Once all the state transition models have been developed, the set of stage 1 state variables consists of the union of all state variables that are selected as predictor variables in these models (Yang 2004).

Table 4.1 Summary of Outcome Models and Transition Functions

	Transf.	Chosen Model	# of state variables	# of decision variables	R^2	Avg. VIF	Max VIF	MSE
PostBDI	Square root	Model C, $\alpha = 0.01$	13	6	0.866	1.367	2.26	0.354
PostOSW	Square root	Model C, $\alpha = 0.01$	9	3	0.815	1.345	1.686	0.26
PostPDA	None	Model C, $\alpha = 0.01$	15	4	0.825	1.587	2.307	0.98
MidBDI	Square root	Model C, $\alpha = 0.05$	26	13	0.908	1.463	2.220	0.262
MidOSW	None	Model C, $\alpha = 0.055$	21	10	0.805	1.731	4.179	16.41
MidPDA	None	Model C, $\alpha = 0.034$	30	12	0.820	1.454	2.126	1.069
$NumPT_1$	Square root	Model C, $\alpha = 0.03$	10	14	0.845	2.365	5.249	0.303
$NumGr_1$	None	Model C, $\alpha = 0.056$	6	10	0.636	1.376	2.000	4.535

4.1.1. BDI Models

BDI stands for Beck Depression Inventory (BDI), described in section 3.1.8. The outcome used in the stage 1 cost objective is the mid-evaluation BDI or MidBDI. The outcome in the stage 2 cost objective is the post-evaluation BDI or PostBDI. The final PostBDI model involved 13 state variables and 7 decision variables, as given below. For Stage 2, a realization of a PostBDI outcome is calculated using the following (Note that "St" preceding a variable name indicates the standardized version of this variable.):

$$\text{Sqrt(PoStBDI)} = 1.4583+0.0781*\text{MidBDI}–1.0518*(\text{StRxGr7}_2*\text{StPainType}) –$$

$$0.2423*(\text{StRxGr4}_1*\text{StPhyDx8})+0.8132*(\text{StProcGr1}_1*\text{StPhyDx3})$$

$+0.3035*(StProcGr9_2*StPastDx7)-0.268*(StProcGr11_2*StPhyDx5)$

$+0.4744*(StRxGr2_2*StNumGr_1)-0.3807*(StRxGr7_2*StPastDx7)-$

$0.4802*(StProcGr9_1*StNumPT_1)+ 0.274*(StRxGr5_2*StPhyDx6)-$

$0.674*(StProcGr4_2*StPreBDI)+ \varepsilon_2$

x_2 : PainType, PhyDx3, PhyDx5, PhyDx6, PhyDx8, PastDx7, PreBDI, $RxGr4_1$, $ProcGr1_1$, $ProcGr9_1$, MidBDI, $NumGr_1$, $NumPT_1$

u_2 : $RxGr2_2$, $RxGr5_2$, $RxGr7_2$, $ProcGr4_2$, $ProcGr9_2$, $ProcGr11_2$

ε_2: Normally distributed with mean zero and variance MSE = 0.354

Table 4.2 lists all the stage 2 state variables (x_2) and stage 2 decision variables (u_2) needed to realize PostBDI. The random variable ε_2 is used to model uncertainty in realizing PostBDI, where MSE is the mean square error from the regression. Any stage 2 state variables that were first observed as stage 1 state variables are simply carried over from stage 1 to 2. These are identity transitions from stage 1 to 2. Three stage 2 state variables (MidBDI, $NumGr_1$, $NumPT_1$) are observed at the end of stage 1, which is the mid-evaluation point. Therefore, transition functions for these three need to be built to transition from at stage 1 to 2. These are developed next in the modeling for stage 1.

Table 4.2 Selected Variables in Stage 2 for PostBDI (BDI at the post-evaluation point)

x_2 : Patients' State Variables Entering Stage 2	
PreBDI	BDI at the pre-evaluation point
MidBDI	BDI at the mid-evaluation point
PainType	Pain Type
PhyDx3	Physical histories of Headache 784.0
PhyDx5	Physical histories of Thoracic724.1
PhyDx6	Physical histories of Lumbar724.2
PhyDx8	Physical histories of Abdominal789.0
PastDx7	Past diagnoses of Myofascial-Fibromyalgia 729.1
$RxGr4_1$	Medication group 4 of Muscle Relaxant at stage 1
$ProcGr1_1$	Injection procedure at stage 1
$ProcGr9_1$	Psychotherapy at stage 1
$NumGr_1$	Number of group sessions in stage 1

Table 4.2 – *Continued*

$NumPT_1$	Number of physical therapy sessions in stage 1
u_2 : Treatment Decision Variables in Stage 2	
$RxGr2_2$	Medication group 2 (NSAID) in stage 2
$RxGr5_2$	Medication group 5 (Antidepressant) in stage 2
$RxGr7_2$	Medication group 7 (Sleeping Pill) in stage 2
$RxGr8_2$	Medication group 8 (Other) in stage 2
$ProcGr4_2$	Stimulation procedure in stage 2
$ProcGr9_2$	Psychotherapy in stage 2
$ProcGr11_2$	Number of additional procedures in stage 2

For Stage 1, realizations of MidBDI, $NumPT_1$, and $NumGr_1$, are calculated using the following (Note that "St" preceding a variable name indicates the standardized version of this variable.):

$$\begin{aligned}\text{Sqrt(MidBDI)} = {} & -0.0948+0.1346*\text{PreBDI}-0.4057*(\text{StRxGr3}_1*\text{StPhyDxoth})- \\ & 1.0919*(\text{StRxGr5}_1*\text{StChildren})-0.24*(\text{StProcGr9}_1*\text{StPhyDx3}) \\ & +0.4595*(\text{StProcGr4}_1*\text{StOnSet})+0.3746*(\text{StRxGr2}_1*\text{StPhyDx6})- \\ & 0.3075*(\text{StRxGr8}_1*\text{StPastDx4})+0.7823*(\text{StRxGr5}_1*\text{StSghxGr2}) \\ & +1.1676*\text{SghxGr2}+0.2857*(\text{StRxGr4}_1*\text{StSghxot1}) \\ & +0.3482*(\text{StRxGr6}_1*\text{StSghxGr1})-0.3099*(\text{StRxGr6}_1*\text{StPhyDx7}) \\ & +0.4987*(\text{StRxGr5}_1*\text{StPhyDx7})-0.3038*(\text{StProcGr1}_1*\text{StLitigat}) \\ & +0.608*(\text{StRxGr7}_1*\text{StDuration})+0.9681*\text{PhyDx9}- \\ & 0.1824*(\text{StProcGr10}_1*\text{StPastDx7})+0.3361*(\text{StProcGr4}_1*\text{StSghxot1})+\varepsilon_{1,1}\end{aligned}$$

$$\begin{aligned}\text{NumPT}_1 = {} & 3.597+3.862*\text{ProcGr10}_1+1.369*(\text{StProcGr9}_1*\text{StPhyDx8})- \\ & 3.698*(\text{StRxGr5}_1*\text{StPreBDI})-0.804*(\text{StProcGr4}_1*\text{StOnSet}) \\ & +0.697*(\text{StProcGr10}_1*\text{StPastDxot})+1.468*(\text{StRxGr5}_1*\text{StMarital})- \\ & 0.959*(\text{StRxGr7}_1*\text{StMarital})-0.094*\text{PreBDI}-0.965*(\text{StRxGr1}_1*\text{StPreBDI}) \\ & +0.396*(\text{StRxGr8}_1*\text{StSghxGr2})-0.516*(\text{StRxGr6}_1*\text{StPastDx11})+ \\ & 0.845*(\text{StRxGr5}_1*\text{StPhyDxoth})+0.771*(\text{StProcGr10}_1*\text{StPreOSW})-\end{aligned}$$

$$0.987*PastDx5 - 0.407*(StProcGr11_1*StChildren) -$$
$$0.38*(StRxGr5_1*StPhyDx3) - 0.319*(StRxGr7_1*StPhyDx9) + \varepsilon_{1,2}$$

$$NumGr_1 = -3.276 - 3.045*(StRxGr5_1*StPrePDA) - 2.935*(StRxGr3_1*StPreBDI) -$$
$$2.194*(StProcGr1_1*StPainType) + 0.744*TxAssign + 0.0152*Duration -$$
$$1.239*(StRxGr1_1*StSghxGr1) + 2.006*(StRxGr1_1*StPastDx11) +$$
$$0.955*(StRxGr4_1*StPhyDx6) + 1.351*(StRxGr7_1*StPhyDx8)$$
$$+0.999*(StRxGr5_1*StPastDx14) + \varepsilon_{1,3}$$

x_1 : Duration, OnSet, PainType, TxAssign, Marital, Children, Litigat, SghxGr1, SghxGr2, Sghxot1, PhyDx3, PhyDx5, PhyDx6, PhyDx7, PhyDx8, PhyDx9, PhyDxoth, PastDx4, PastDx5, PastDx7, PastDx11, PastDx14, PastDxot, PreBDI, PreOSW, PrePDA

u_1 : $RxGr1_1$, $RxGr2_1$, $RxGr3_1$, $RxGr4_1$, $RxGr5_1$, $RxGr6_1$, $RxGr7_1$, $RxGr8_1$, $ProcGr1_1$, $ProcGr4_1$, $ProcGr9_1$, $ProcGr10_1$, $ProcGr11_1$

$\varepsilon_{1,1}$: Normally distributed with mean zero and variance MSE = 0.262

$\varepsilon_{1,2}$: Normally distributed with mean zero and variance MSE = 0.303

$\varepsilon_{1,3}$: Normally distributed with mean zero and variance MSE = 4.545

Table 4.3 lists all the stage 1 state variables (x_1) and stage 1 decision variables (u_1) needed to realize MidBDI, $NumGr_1$, and $NumPT_1$. The random variables $\varepsilon_{1,1}$, $\varepsilon_{1,2}$, and $\varepsilon_{1,3}$ are used to model uncertainty in realizing these variables. There are 26 state variables and 13 decision variables in stage 1. Seven of the stage 1 state variables follow identity transitions to stage 2 (PreBDI, PhyDx3, PainType, PhyDx5, PhyDx6, PastDx7, PhyDx8), and three of the stage 1 decision variables follow identity transitions to stage 2 ($ProcGr9_1$, $RxGr4_1$, $ProcGr1_1$). The square root transformation was applied to both the PostBDI and MidBDI models to remedy a nonconstant variance issue.

Table 4.3 Selected Variables in Stage 1 for MidBDI (BDI at the mid-evaluation point), $NumPT_1$ (Number of physical therapy sessions), $NumGr_1$ (Number of group sessions), and to be passed to Stage 2

x_1 : Patients' State Variables Entering Stage 1	
PreBDI	BDI at the pre-evaluation point
PreOSW	OSW at the pre-evaluation point
PrePDA	PDA at the pre-evaluation point
Duration	Duration
OnSet	OnSet
PainType	PainType
TxAssign	TxAssign
Marital	Marital
Children	Children
Litigat	Litigat
SghxGr1	Surgical history group 1 (Discectomy)
SghxGr2	Surgical history group 2 (Fusion)
Sghxot1	# of additional surgeries related to condition
PhyDx3	Physical histories of Headache 784.0
PhyDx5	Physical histories of Thoracic724.1
PhyDx6	Physical histories of Lumbar724.2
PhyDx7	Physical histories of Myofascial-Fibromyalgia 729.1
PhyDx8	Physical histories of Abdominal789.0
PhyDx9	Physical histories of Pelvic (Female) 625.9
PhyDxoth	Number of additional physical diagnoses
PastDx4	Past diagnoses of Cervical723.1
PastDx5	Past diagnoses of Thoracic724.1
PastDx7	Past diagnoses of Myofascial-Fibromyalgia 729.1
PastDx11	Past diagnoses of Abdominal789.0
PastDx14	Past diagnoses of Pelvic (Female) 625.9
PastDxot	Number of additional diagnoses
u_1 : Treatment Decision Variables in Stage 1	
$RxGr1_1$	Medication group 1 (Tramadol) in stage 1
$RxGr2_1$	Medication group 2 (NSAID) in stage 1
$RxGr3_1$	Medication group 3 (Narcotic) in stage 1
$RxGr4_1$	Medication group 4 (Muscle Relaxant in stage 1
$RxGr5_1$	Medication group 5 (Antidepressant) in stage 1
$RxGr6_1$	Medication group 6 (Tranquilizer) in stage 1
$RxGr7_1$	Medication group 7 (Sleeping Pill) in stage 1

Table 4.3 – *Continued*

$RxGr8_1$	Medication group 8 (Other) in stage 1
$ProcGr1_1$	Injection procedure in stage 1
$ProcGr4_1$	Stimulation procedure in stage 1
$ProcGr9_1$	Psychotherapy in stage 1
$ProcGr10_1$	Physical therapy in stage 1
$ProcGr11_1$	Number of additional procedures in stage 1

4.1.2. OSW Models

OSW stands for Oswestry Pain Disability Questionnaire, described in section 3.1.8. The outcome used in the stage 1 cost objective is the mid-evaluation OSW or MidOSW. The outcome in the stage 2 cost objective is the post-evaluation OSW or PostOSW. The final PostOSW model involved 8 state variables and 3 decision variables, as given below. For stage 2, a realization of a PostOSW outcome is calculated using the following (Note that "St" preceding a variable name indicates the standardized version of this variable.):

$$\begin{aligned}\text{Sqrt(PostOSW)} = {} & 2.55 + 0.105*\text{MidOSW} - 0.5367*(\text{StProcGr9}_2*\text{StMidOSW}) + \\ & 0.423*(\text{StProcGr9}_2*\text{StMarital}) + 0.49*(\text{StRxGr2}_1*\text{StNumGr}_1) - \\ & 0.3174*(\text{StRxGr3}_2*\text{StSghxGr1}) - 0.6736*(\text{StRxGr4}_2*\text{StPreOSW}) - \\ & 0.3873*(\text{StProcGr4}_1*\text{StSghxot2}) + \varepsilon_2\end{aligned}$$

x_2 : Marital, SghxGr1, Sghxot2, PreOSW, $RxGr2_1$, $ProcGr4_1$, MidOSW, $NumGr_1$,

u_2 : $RxGr3_2$, $RxGr4_2$, $ProcGr9_2$

ε_2 : Normally distributed with mean zero and variance MSE = 0.26

Table 4.4 lists all the stage 2 state variables (x_2) and stage 2 decision variables (u_2) needed to realize PostOSW. The random variable ε_2 is used to model uncertainty in realizing PostBDI, where MSE is the mean square error from the regression. Any stage 2 state variables that were first observed as stage 1 state variables are simply carried over from stage 1 to 2. These are identity transitions from stage 1 to 2. Two stage 2 state variables (MidOSW, $NumGr_1$) are observed at the end of stage 1, which is the mid-evaluation point. Therefore, transition

functions for these two need to be built to transition from at stage 1 to 2. These are developed next in the modeling for stage 1.

Table 4.4 Selected Variables in Stage 2 for PostOSW (OSW at the post-evaluation point)

x_2 : Patients' State Variables Entering Stage 2	
PreOSW	OSW at the pre-evaluation point
MidOSW	OSW at the mid-evaluation point
Marital	Marital
SghxGr1	Surgical history group 1 (Discectomy)
Sghxot2	# of additional NOT surgeries related to condition
$RxGr2_1$	Medication group 2 (NSAID) in stage 1
$ProcGr4_1$	Stimulation procedure in stage 1
$NumGr_1$	Number of group sessions in stage 1
u_2 : Treatment Decision Variables in Stage 2 (OSW)	
$RxGr3_2$	Medication group 3 (Narcotic) in stage 2
$RxGr4_2$	Medication group 4 (Muscle Relaxant) in stage 2
$ProcGr9_2$	Psychotherapy in stage 2

For stage 1, realizations of MidOSW and $NumGr_1$ are calculated using the following (Note that "St" preceding a variable name indicates the standardized version of this variable.):

$$\begin{aligned}MidOSW = {} & 22.176 - 12.243*(StProcGr1_1*StPreOSW) - 8.666*(StRxGr8_1*StPreBDI) - \\ & 2.473*(StRxGr7_1*StSghxGr2) - 2.012*Sghxot2 - 4.243*(StRxGr8_1*StAge) + \\ & 3.673*(StProcGr9_1*StPrePDA) + 2.501*(StProcGr4_1*StPastDx3) - \\ & 2.987*(StRxGr3_1*StPhyDxoth) - 2.408*(StProcGr9_1*StSghxGr4) + \\ & 3.253*(StProcGr9_1*StPhyDx9) - 1.742*(StProcGr9_1*StSghxGr1) - \\ & 2.373*Sghxot1 + \varepsilon_{1,1}\end{aligned}$$

$$\begin{aligned}NumGr_1 = {} & -3.276 - 3.045*(StRxGr5_1*StPrePDA) - 2.935*(StRxGr3_1*StPreBDI) - \\ & 2.194*(StProcGr1_1*StPainType) + 0.744*TxAssign + 0.0152*Duration - \\ & 1.239*(StRxGr1_1*StSghxGr1) + 2.006*(StRxGr1_1*StPastDx11) + \\ & 0.955*(StRxGr4_1*StPhyDx6) + 1.351*(StRxGr7_1*StPhyDx8) + 0.999*(StRxGr5_1*St \\ & PastDx14) + \varepsilon_{1,2}\end{aligned}$$

x_1 : Duration, PainType, TxAssign, Age, Marital, SghxGr1, SghxGr2, SghxGr4, Sghxot1, Sghxot2, PhyDx6, PhyDx8, PhyDx9, PhyDxoth, PastDx3, PastDx11, PastDx14, PreBDI, PreOSW, PrePDA,

u_1 : $RxGr1_1$, $RxGr2_1$, $RxGr3_1$, $RxGr4_1$, $RxGr5_1$, $RxGr7_1$, $RxGr8_1$, $ProcGr1_1$, $ProcGr4_1$, $ProcGr9_1$,

$\varepsilon_{1,1}$: Normally distributed with mean zero and variance MSE = 16.4

$\varepsilon_{1,2}$: Normally distributed with mean zero and variance MSE = 4.54

Table 4.5 lists all the stage 1 state variables (x_1) and stage 1 decision variables (u_1) needed to realize MidOSW and $NumGr_1$. The random variables $\varepsilon_{1,1}$ and $\varepsilon_{1,2}$ are used to model uncertainty in realizing these variables. There are 20 state variables and 11 decision variables in stage 1. Five of the stage 1 state variables follow identity transitions to stage 2 (PreOSW, Sghxot2, SghxGr1, MidOSW, Marital), and two of the stage 1 decision variables follow identity transitions to stage 2 ($ProcGr4_1$, $RxGr2_1$). The square root transformation was applied to the PostOSW model to remedy a nonconstant variance issue.

Table 4.5 Selected Variables in Stage 1 for MidOSW (OSW at the mid-evaluation point), $NumGr_1$ (Number of group sessions), and to be passed to Stage 2

x_1 : Patients' State Variables Entering Stage 1	
PreBDI	BDI at the pre-evaluation point
PreOSW	OSW at the pre-evaluation point
PrePDA	PDA at the pre-evaluation point
Duration	Duration
PainType	Pain Type
TxAssign	TxAssign
Age	Age
Marital	Marital
SghxGr1	Surgical history group 1 (Discectomy)
SghxGr2	Surgical history group 2 (Fusion)
SghxGr4	Surgical history group 4 (Neural decompression)
Sghxot1	# of additional surgeries related to condition
Sghxot2	# of additional NOT surgeries related to condition
PhyDx6	Physical histories of Lumbar724.2

Table 4.5 – *Continued*

PhyDx8	Physical histories of Abdominal789.0
PhyDx9	Physical histories of Pelvic (Female) 625.9
PhyDxoth	Number of additional physical diagnoses
PastDx3	Past diagnoses of Headache 784.0
PastDx11	Past diagnoses of Abdominal789.0
PastDx14	Past diagnoses of Pelvic (Female) 625.9
u_1 : Treatment Decision Variables in Stage 1	
$RxGr1_1$	Medication group 1 (Tramadol) in stage 1
$RxGr2_1$	Medication group 2 (NSAID) in stage 1
$RxGr3_1$	Medication group 3 (Narcotic) in stage 1
$RxGr4_1$	Medication group 4 (Muscle Relaxant in stage 1
$RxGr5_1$	Medication group 5 (Antidepressant) in stage 1
$RxGr6_1$	Medication group 6 (Tranquilizer) in stage 1
$RxGr7_1$	Medication group 7 (Sleeping Pill) in stage 1
$RxGr8_1$	Medication group 8 (Other) in stage 1
$ProcGr1_1$	Injection procedure in stage 1
$ProcGr4_1$	Stimulation procedure in stage 1
$ProcGr9_1$	Psychotherapy in stage 1

4.1.3. PDA Models

PDA stands for Pain Drawing Analogue, described in section 3.1.8. The outcome used in the stage 1 cost objective is the mid-evaluation PDA or MidPDA. The outcome in the stage 2 cost objective is the post-evaluation PDA or PostPDA. The final PostPDA model involved 15 state variables and 4 decision variables, as given below; also the details on its regression model assumptions are in Appendix A.

For stage 2, a realization of a PostPDA outcome is calculated using the following (Note that "St" preceding a variable name indicates the standardized version of this variable.):

$$\begin{aligned}PostPDA = {} & 5.8 - 2.1422*(StProcGr1_1*StMidPDA) - 0.5718*(StRxGr3_2*StPhyDx8) + \\ & 1.2485*(StRxGr4_1*StAge) - 2.3553*(StProcGr4_2*StMidOSW) + \\ & 0.9233*(StProcGr1_1*StPastDx7) + 1.0274*(StProcGr9_1*StPastDx3) - \\ & 0.6991*(StRxGr4_1*StPastDx7) - 0.9363*(StProcGr10_1*StPhyDx3) - \\ & 1.2886*(StProcGr1_1*StPhyDx5) - 0.8645*(StRxGr5_2*StNumGr_1) + \\ & 0.9995*(StRxGr4_2*StPastDx5) + 0.4546*(StRxGr5_2*StPastDx14) + \varepsilon_2\end{aligned}$$

x_2 : Age, PhyDx3, PhyDx5, PhyDx8, PastDx3, PastDx5, PastDx7, PastDx14, $RxGr4_1$, $ProcGr1_1$, $ProcGr9_1$, $ProcGr10_1$, MidOSW, MidPDA, $NumGr_1$

u_2 : $RxGr3_2$, $RxGr4_2$, $RxGr5_2$, $ProcGr4_2$,

ε_2 : Normally distributed with mean zero and variance MSE = 0.98

Table 4.6 lists all the stage 2 state variables (x_2) and stage 2 decision variables (u_2) needed to realize PostPDA. The random variable ε_2 is used to model uncertainty in realizing PostBDI, where MSE is the mean square error from the regression. Any stage 2 state variables that were first observed as stage 1 state variables are simply carried over from stage 1 to 2. These are identity transitions from stage 1 to 2. Three stage 2 state variables (MidPDA, MidOSW, $NumGr_1$) are observed at the end of stage 1, which is the mid-evaluation point. Therefore, transition functions for these three need to be built to transition from at stage 1 to 2. These are developed next in the modeling for stage 1.

Table 4.6 Selected Variables in Stage 2 for PostPDA (PDA at the post-evaluation point)

x_2 : Patients' State Variables Entering Stage 2	
MidOSW	OSW at the mid-evaluation point
MidPDA	PDA at the mid-evaluation point
Age	Age
PhyDx3	Physical histories of Headache 784.0
PhyDx5	Physical histories of Thoracic724.1
PhyDx8	Physical histories of Abdominal789.0
PastDx3	Past diagnoses of Headache 784.0
PastDx5	Past diagnoses of Thoracic724.1
PastDx7	Past diagnoses of Myofascial-Fibromyalgia 729.1
PastDx14	Past diagnoses of Pelvic (Female) 625.9
$RxGr4_1$	Medication group 4 of Muscle Relaxant in stage 1
$ProcGr1_1$	Injection procedure in stage 1
$ProcGr9_1$	Psychotherapy in stage 1
$ProcGr10_1$	Physical therapy in stage 1
$NumGr_1$	Number of group sessions in stage 1
u_2 : Treatment Decision Variables in Stage 2 (PDA)	
$RxGr3_2$	Medication group 3 (Narcotic) in stage 2

Table 4.6 – *Continued*

$RxGr4_2$	Medication group 4 (Muscle Relaxant) in stage 2
$RxGr5_2$	Medication group 5 (Antidepressant) in stage 2
$ProcGr4_2$	Stimulation procedure in stage 2

For stage 1, realizations of MidPDA, MidOSW, and $NumGr_1$, are calculated using the following (Note that "St" preceding a variable name indicates the standardized version of this variable.):

$$\begin{aligned}
MidPDA = {} & 6.858 - 2.394*(StRxGr6_1*StPreOSW) - 0.69*(StRxGr3_1*StSghxGr4) + 1.036 \\
& *(StProcGr9_1*StPrePDA) - 1.735*(StRxGr8_1*StTxAssign) + \\
& 2.061*(StRxGr5_1*StPainType) + 1.148*(StRxGr6_1*StSghxot2) - \\
& 0.4545*(StRxGr3_1*StPastDx4) - 0.607*(StProcGr10_1*StPastDx7) - \\
& 0.787*(StRxGr1_1*StSghxGr1) - 1.221*(StRxGr3_1*StChildren) + \\
& 0.684*(StRxGr2_1*StPastDx14) - 0.926*(StRxGr4_1*StMarital) - \\
& 1.106*(StRxGr6_1*StPreBDI) + 0.629*(StProcGr1_1*StPastDx6) + \\
& 0.885*(StRxGr8_1*StAge) - 0.377*(StRxGr4_1*StPhyDx6) - \\
& 0.471*(StRxGr6_1*StPastDx11) + \varepsilon_{1,1}
\end{aligned}$$

$$\begin{aligned}
MidOSW = {} & 22.176 - 12.243*(StProcGr1_1*StPreOSW) - 8.666*(StRxGr8_1*StPreBDI) - \\
& 2.473*(StRxGr7_1*StSghxGr2) - 0.012*Sghxot2 - 4.243*(StRxGr8_1*StAge) + \\
& 3.673*(StProcGr9_1*StPrePDA) + 2.501*(StProcGr4_1*StPastDx3) - \\
& 2.987*(StRxGr3_1*StPhyDxoth) - 2.408*(StProcGr9_1*StSghxGr4) + \\
& 3.253*(StProcGr9_1*StPhyDx9) - 1.742*(StProcGr9_1*StSghxGr1) - \\
& 2.373*Sghxot1 + \varepsilon_{1,2}
\end{aligned}$$

$$\begin{aligned}
NumGr_1 = {} & -3.276 - 3.045*(StRxGr5_1*StPrePDA) - 2.935*(StRxGr3_1*StPreBDI) - \\
& 2.194*(StProcGr1_1*StPainType) + 0.744*TxAssign + 0.0152*Duration - \\
& 1.239*(StRxGr1_1*StSghxGr1) + 2.006*(StRxGr1_1*StPastDx11) + \\
& 0.955*(StRxGr4_1*StPhyDx6) + 1.351*(StRxGr7_1*StPhyDx8) + \\
& 0.999*(StRxGr5_1*StPastDx14) + \varepsilon_{1,3}
\end{aligned}$$

x_1 : Duration, PainType, TxAssign, Age, Marital, Children, SghxGr1, SghxGr2, SghxGr4, Sghxot1, Sghxot2, PhyDx3, PhyDx5, PhyDx6, PhyDx8, PhyDx9, PhyDxoth, PastDx3, PastDx4, PastDx5, PastDx6, PastDx7, PastDx11, PastDx14, PreBDI, PreOSW, PrePDA

u_1 : $RxGr1_1$, $RxGr2_1$, $RxGr3_1$, $RxGr4_1$, $RxGr5_1$, $RxGr6_1$, $RxGr7_1$, $RxGr8_1$, $ProcGr1_1$, $ProcGr4_1$, $ProcGr9_1$, $ProcGr10_1$

$\varepsilon_{1,1}$: Normally distributed with mean zero and variance MSE = 1.069.

$\varepsilon_{1,2}$: Normally distributed with mean zero and variance MSE = 16.4.

$\varepsilon_{1,3}$: Normally distributed with mean zero and variance MSE = 4.535.

Table 4.7 lists all the stage 1 state variables (x_1) and stage 1 decision variables (u_1) needed to realize MidPDA, MidOSW, and $NumGr_1$. The random variables $\varepsilon_{1,1}$, $\varepsilon_{1,2}$, and $\varepsilon_{1,3}$ are used to model uncertainty in realizing these variables. There are 29 state variables and 12 decision variables in stage 1. Eight of the stage 1 state variables follow identity transitions to stage 2 (PhyDx8, Age, PastDx7, PastDx3, PhyDx3, PhyDx5, PastDx5, PastDx14), and four of the stage 1 decision variables follow identity transitions to stage 2 ($ProcGr9_1$, $ProcGr10_1$, $RxGr4_1$, $ProcGr1_1$).

Table 4.7 Selected Variables in Stage 1 for MidPDA (PDA at the mid-evaluation point), MidOSW (OSW at the post-evaluation point), $NumGr_1$ (Number of group sessions), and to be passed to Stage 2

x_1 : Patients' State Variables Entering Stage 1 (PDA)	
Duration	Duration
PreBDI	BDI at the pre-evaluation point
PreOSW	OSW at the pre-evaluation point
PrePDA	PDA at the pre-evaluation point
PainType	PainType
TxAssign	TxAssign
Age	Age
Marital	Marital
Children	Children
SghxGr1	Surgical history group 1 (Discectomy)

Table 4.7 – *Continued*

SghxGr2	Surgical history group 2 (Fusion)
SghxGr4	Surgical history group 4 (Neural decompression)
Sghxot1	# of additional surgeries related to condition
Sghxot2	# of additional NOT surgeries related to condition
PhyDx3	Physical histories of Headache 784.0
PhyDx5	Physical histories of Thoracic724.1
PhyDx6	Physical histories of Lumbar724.2
PhyDx8	Physical histories of Abdominal789.0
PhyDx9	Physical histories of Pelvic (Female) 625.9
PhyDx11	Physical histories of Osteoarthritis716.9
PhyDx14	Physical histories of Upper Extremity 729.5
PhyDxoth	Number of additional physical diagnoses
PastDx3	Past diagnoses of Headache 784.0
PastDx4	Past diagnoses of Cervical723.1
PastDx5	Past diagnoses of Thoracic724.1
PastDx6	Past diagnoses of Lumbar724.2
PastDx7	Past diagnoses of Myofascial-Fibromyalgia 729.1
PastDx11	Past diagnoses of Abdominal789.0
PastDx14	Past diagnoses of Pelvic (Female) 625.9
PastDxot	Number of additional diagnoses
u_1 : Treatment Decision Variables in Stage 1 (PDA)	
$RxGr1_1$	Medication group 1 (Tramadol) in stage 1
$RxGr2_1$	Medication group 2 (NSAID) in stage 1
$RxGr3_1$	Medication group 3 (Narcotic) in stage 1
$RxGr4_1$	Medication group 4 (Muscle Relaxant in stage 1
$RxGr5_1$	Medication group 5 (Antidepressant) in stage 1
$RxGr6_1$	Medication group 6 (Tranquilizer) in stage 1
$RxGr7_1$	Medication group 7 (Sleeping Pill) in stage 1
$RxGr8_1$	Medication group 8 (Other) in stage 1
$ProcGr1_1$	Injection procedure in stage 1
$ProcGr4_1$	Stimulation procedure in stage 1
$ProcGr9_1$	Psychotherapy in stage 1
$ProcGr10_1$	Physical therapy in stage 1

4.2 Approximating the Stage 2 Future Value Function

As mentioned earlier in this chapter, only the stage 2 SDP future value function needs to be approximated. An SDP model is developed and solved separately for each of the three

outcome measures. The stage 2 future value function depends on the stage 2 state variables. Given the specific set of stage 2 state variables for a specific outcome measure, an appropriate dimension Latin hypercube experimental design with 50 points was constructed within the stage 2 state variable space for each of the three outcome measures. Following the algorithm in Figure 2.3, the 50 points in the Latin hypercube design constitute 50 state space discretization points. For each point, the stage 2 expected cost minimization in section 3.2.2 is conducted using the total cost function that sums the treatment utilization function in section 3.2.4 and the penalty cost function in section 3.2.5. One tricky issue is representing the expected value of the cost. A crude estimate of the expected value is calculated by averaging the cost function over 10 realizations of the random variable ε_2 in the stage 2 outcome measure models (PostBDI, PostOSW, PostPDA) from section 4.1 Specifically, the 10 realizations for each outcome measure are as follows:

Sqrt(PostBDI) ε_2 : 0.26, -0.99, 0.075, 0.17, -0.682, 0.708, 0.707, -0.022, 0.195, 0.104.

Sqrt(PostOSW) ε_2 : 0.095, 0.37, -0.3, 1.113, -0.07, 0.058, 0.544, 0.03, -0.049, -0.424.

PDA ε_2 : 0.291, -1.323, 0.707, 1.607, -0.685, 0.849, 1.241, -1.578, -1.426, 0.565.

For each discretization point, the minimized expected cost objective is a point on the future value function.

Given these data, the approximation of future value function at stage 2 is constructed over the stage 2 state variable space using an ANN model Each ANN model is structured with 1 hidden layer with 20 hidden nodes and 1000 epochs to estimate the model parameters.

4.3 Simulating Forward On-line SDP Re-optimization

The general re-optimization procedure is illustrated in Figure 4.1. The notation is the same as defined in the section 2.3.1, where *x* denotes the state variables, *u* denotes the decision variables, *ε* denotes the random vectors, *t* indexes the different stages, and *T* represents the last stage. In step 1, we solve the minimize the future expected value of cost function $c_t(\cdot)$, and the approximation of the future value function of the next stage, $\hat{F}_{t+1}(\cdot)$. The

future value function approximation was constructed in section 4.2. The transition functions described in section 4.1 are used to conduct state transitions.

1. For stage, $t = 1, \dots, T-1$,
   a) Solve $min_{u_t} E\{c_t(x_t, u_t, \varepsilon_t) + \hat{F}_{t+1}(f(x_t, u_t, \varepsilon_t))\}$ for u_t,
   b) Calculate $x_{t+1} = f(x_t, u_t, \varepsilon_t)$
2. For stage *T*, solve $min_{u_T} E\{c_T(x_T, u_T, \varepsilon_t)\}$ for u_T.

Figure 4.1 A general re-optimization algorithm for solving the optimal control policy (Yang 2004).

In the case of adaptive pain management, we simulated all 89 patients in our data set. For each patient, the stage 1 state variables are set based on the actual data for that patient. Then we re-optimize the decision variables in stage 1 using re-optimization. As in section 4.2, the expected value is approximated as the average over 10 realizations of the relevant random variables. In stage 1, there are multiple random variables. Specifically, the components of the multi-dimensional random vectors are as follows for the BDI case:

Sqrt(MidBDI) $\varepsilon_{1,1}$: -0.067, -0.326, -0.487, -0.42, -0.222, 0.168, -0.514, -0.61, 0.029, -0.578.

$NumPT_1$ $\varepsilon_{1,2}$: 0.215, -0.308, 0.43, -0.146, -0.917, 0.129, -0.522, -0.582, -0.67, -0.743.

$NumGr_1$ $\varepsilon_{1,3}$: 0.187, 0.945, 1.212, -2.529, 0.267, 0.046, -0.797, 3.136, -0.088, -0.556.

The components of the multi-dimensional random vectors are as follows for the OSW case:

MidOSW $\varepsilon_{1,1}$: 3.863, 0.521, 2.659, -4.731, -1.866, -1.063, -4.915, -5.345, 3.772, 0.046.

$NumGr_1$ $\varepsilon_{1,2}$: 1.374, 1.716, 0.493, -2.108, 2.853, 0.617, 3.149, 2.423, -1.457, -2.751.

The components of the multi-dimensional random vectors are as follows for the PDA case:

MidPDA $\varepsilon_{1,1}$: 1.647, 1.053, -1.634, -0.081, -0.705, -1.059, -1.276, 0.299, -0.444, 0.058.

MidOSW $\varepsilon_{1,2}$: -1.490, -1.884, 1.503, 2.950, 8.556, -5.498, -4.143, 4.204, -1.579, -5.596.

$NumGr_1$ $\varepsilon_{1,3}$: 0.672, 3.308, 1.508, 4.168, 1.074, 3.971, -0.724, -2.427, -0.450, 2.535.

Once the re-optimized stage 1 decision variables are obtained, we can simulate a realization of the state transition to stage 2, where the random variables are sampled from the normal distributions specified in section 4.1. Given the realized stage 2 state variables, we can re-optimize the decision variables in stage 2 and obtain the final outcomes. For each patient, 1000 simulation runs are conducted, and averages of outcome pain level and decision variables are calculated over the 1000 simulation runs for each patient.

4.4 Forward SDP Re-optimization Results

In this section, the results of the forward SDP re-optimization runs for the 89 patients are compared to the original values in the data. In each table, the first column indexes the patient. The second column gives the pre-evaluation outcome values that are observed at the beginning of stage 1. The third main column shows treatment utilization (TU), the SDP re-optimization outcome at end of stage 1, and mid-evaluation outcome from the original data. The final major column provides TU, the SDP re-optimized outcome at the end of stage 2, and post-evaluation outcome from the original data. Appendix B tables the re-optimized values of the decision variables for each stage, averaged over the 1000 simulations. However, please note that the notations for the decision variables for each stage are not identically the same within three outcome models. For example, the u1 in the MidBDI is RxGr31, but the u1 in the MidOSW is $ProcGr1_1$. From the table, we can illustrate what treatments should be recommended for different patients.

4.4.1. Re-optimization Result of BDI Model

Table 4.8 presents the results for the BDI outcome. It can be seen that only the first patient has a final BDI outcome above 10. Most patients require no treatment actions in stage 2. This is because after stage 1, the values of MidBDI for most patients are already around or lower than 10. On the other hand, two patients' outcome values are higher than the original dataset (patient 19 and 76), but they are still below than 10, which is considered to be normal.

In addition, if we take a look in Appendix B, some treatments are barely used at stage 1. They are ProcGr9, RxGr8, ProcGr10, RxGr1 and ProcGr11.

Table 4.8 Comparison of BDI Model: Treatment utilization (TU), SDP re-optimization outcome (SDP), and Original data outcome (Orig).

	Pre	MidBDI			PostBDI				
	BDI	TU	SDP	Orig.	TU	StD	SDP	StD	Orig.
1	46	14	21.51	50	0.4	0.05	10.86	0.06	46
2	34	3.8	15.07	25	0	0	5.68	1.00	34
3	4	1.8	0.32	4	0	0	2.03	0.37	6
4	6	2.4	4.22	6	0	0	1.08	0.33	0
5	6	0	2.43	1	0	0	1.19	0.45	12
6	18	2	11.83	16	0	0	0.04	0.06	1
7	20	4.6	15.80	20	0	0	1.81	0.54	21
8	25	0	4.10	10	0	0	1.60	0.53	9
9	9	1.6	6.43	9	0	0	0.24	0.18	1
10	20	0	9.41	11	0	0	4.16	0.82	21
11	31	1.4	14.43	31	0	0	8.63	1.18	35
12	18	0.7	10.39	19	0	0	5.23	0.96	10
13	11	0.1	3.96	9	0	0	3.15	0.74	3
14	11	0	1.19	7	0	0	0.09	0.11	2
15	28	4.2	14.46	31	0	0	4.68	0.91	16
16	33	4.4	15.64	18	0	0	0.57	0.31	21
17	5	0.3	8.25	4	0	0	2.45	0.61	7
18	20	0.2	9.98	16	0	0	2.49	0.66	16
19	40	3.4	15.36	27	0	0	6.75	1.09	4
20	12	0.5	7.19	9	0	0	1.33	0.43	10
21	14	0	5.50	5	0	0	0.28	0.21	5
22	18	0.3	5.60	15	0	0	1.97	0.58	18
23	4	0.8	2.15	4	0	0	0.01	0.03	2
24	7	0.7	6.10	2	0	0	0.19	0.11	1
25	18	0	5.12	6	0	0	1.81	0.47	4
26	18	0	1.59	25	0	0	1.89	0.57	22
27	21	0.1	9.65	18	0	0	2.74	0.69	17
28	4	0	3.41	2	0	0	0.93	0.18	1
29	5	1.3	4.51	3	0	0	1.33	0.48	4
30	21	4.3	13.39	19	0	0	5.43	0.97	15
31	11	0.4	1.29	6	0	0	2.78	0.40	7
32	5	1.5	6.34	6	0	0	5.22	0.95	6

Table 4.8 – *Continued*

33	9	0.8	7.63	10	0	0	2.80	0.70	8
34	23	0	7.89	6	0	0	4.40	0.88	10
35	11	0.8	6.39	9	0	0	6.34	0.50	20
36	13	2.7	7.95	13	0	0	4.73	0.86	17
37	9	1	1.53	10	0	0	2.14	0.53	12
38	6	1.8	1.03	13	0	0	1.94	0.48	11
39	36	4.1	15.80	31	0	0	7.06	1.11	27
40	26	2.1	13.90	25	0	0	6.47	0.63	19
41	16	0.1	10.35	12	0	0	3.43	0.76	12
42	11	0.1	3.87	18	0	0	2.74	0.70	15
43	0	0	0.23	0	0	0	1.60	0.30	0
44	16	0	6.06	7	0	0	5.16	0.90	8
45	10	0.8	0.52	5	0	0	2.14	0.52	5
46	15	0.1	11.10	8	0	0	3.40	0.77	5
47	18	0	5.14	1	0	0	2.43	0.64	0
48	11	2.7	6.57	19	0	0	2.80	0.60	11
49	15	0	5.25	5	0	0	4.93	0.93	2
50	20	1.2	11.52	9	0	0	5.61	0.97	9
51	23	0	7.97	10	0	0	2.01	0.60	11
52	0	1	0.00	0	0	0	0.05	0.03	1
53	18	0	1.57	9	0	0	2.46	0.22	6
54	39	3.7	16.12	17	0	0	4.57	0.90	8
55	12	0.8	4.17	17	0	0	1.14	0.38	1
56	1	0	8.99	1	0	0	1.98	0.49	4
57	11	0.6	8.44	3	0	0	0.21	0.18	1
58	13	0	3.82	12	0	0	0.35	0.21	2
59	10	0	4.21	11	0	0	2.42	0.58	2
60	21	2.6	11.85	23	0	0	1.84	0.56	16
61	5	0.2	0.00	0	0	0	2.44	0.40	1
62	1	0	3.41	0	0	0	0.72	0.32	0
63	32	2.3	14.66	34	0	0	6.29	0.99	15
64	30	1.9	13.54	38	0	0	2.58	0.67	24
65	27	1.8	12.83	19	0	0	8.70	1.01	9
66	11	3.3	10.47	17	0	0	4.28	0.86	9
67	11	1.4	5.23	4	0	0	2.04	0.58	6
68	18	1.4	10.44	9	0	0	3.32	0.77	3
69	7	1.3	4.71	3	0	0	2.37	0.65	10
70	6	1.3	0.13	6	0	0	1.62	0.43	6
71	10	0.2	3.93	6	0	0	3.69	0.79	7
72	7	0.6	1.22	5	0	0	1.39	0.49	0

Table 4.8 – *Continued*

73	4	2.7	0.10	0	0	0	2.03	0.38	4
74	3	0.3	1.92	2	0	0	0.42	0.26	4
75	4	1.6	1.34	2	0	0	1.04	0.42	2
76	24	0.1	11.03	2	0	0	3.02	0.73	2
77	12	0	4.25	4	0	0	2.02	0.58	7
78	2	0.4	1.35	0	0	0	0.16	0.16	0
79	7	0.5	1.40	3	0	0	0.69	0.30	0
80	3	3.3	0.01	1	0	0	0.86	0.17	0
81	16	1.1	9.82	12	0	0	2.89	0.60	7
82	14	0	2.25	12	0	0	2.21	0.61	14
83	14	0.3	10.14	4	0	0	0.24	0.20	0
84	7	2.4	1.84	2	0	0	3.65	0.75	4
85	10	0	2.30	6	0	0	2.83	0.70	8
86	4	0.1	0.00	2	0	0	1.15	0.22	0
87	29	0	8.65	12	0	0	2.88	0.71	8
88	13	0.8	8.36	11	0	0	2.43	0.64	15
89	12	1.2	8.24	6	0	0	1.37	0.44	6

4.4.2. Re-optimization result of OSW Model

Table 4.9 presents the results for the OSW outcome. Many patients have zero treatment utilization, which means no treatment was applied. Taking a close look on their MidOSW, most of them have values around 10. However, two treatments are hardly used in stage 1; RxGr4 and RxGr5; ProcGr9 only been used for three patients.

Table 4.9 Comparison of OSW Model: Treatment utilization (TU), SDP re-optimization outcome (SDP), and Original data outcome (Orig).

	Pre	MidOSW			PostOSW				
	OSW	TU	SDP	Orig.	TU	StD	SDP	StD	Orig.
1	22	0.33	13.40	29	0	0	9.85	1.39	29
2	35	3.61	12.47	35	0	0	9.94	1.40	39
3	22	0.78	8.94	13	0	0	9.92	1.14	8
4	29	6.49	5.19	14	0	0	5.97	1.08	13
5	20	0.1	13.51	19	0	0	9.45	1.35	21
6	30	0.17	12.26	14	0	0	10.97	1.32	8
7	6	0	0.00	6	0	0	0.88	0.37	8
8	31	3.74	20.38	33	1.361	0.38	21.80	1.44	30
9	17	2.9	10.85	21	0	0	5.58	0.72	17

Table 4.9 – *Continued*

10	29	3.44	13.05	26	0.009	0.02	18.30	1.59	20
11	3	1.68	5.08	16	0	0	3.03	0.44	16
12	26	1.28	16.41	25	0	0	13.51	1.63	20
13	39	1.92	12.64	28	0.003	0.02	12.51	1.55	21
14	14	0	13.14	17	0.011	0.04	13.14	1.53	14
15	20	0.18	14.39	28	0	0	7.99	1.25	7
16	25	0	13.04	16	0	0	6.29	1.11	18
17	20	1.41	16.58	17	0.63	0.22	19.24	1.38	16
18	24	0.81	19.68	24	0	0	16.66	1.81	20
19	25	0.86	17.16	25	0	0	6.73	1.15	14
20	9	1.11	7.17	6	0	0	4.92	0.52	4
21	27	0.01	15.30	14	0	0	11.10	1.45	7
22	29	5.08	18.30	26	0	0	13.53	1.61	23
23	4	1.58	9.32	3	0	0	5.89	0.55	3
24	5	0.97	4.72	0	0	0	3.21	0.37	0
25	17	0.97	8.81	3	0	0	7.27	0.76	6
26	25	0.89	16.69	25	0.437	0.22	18.01	1.47	26
27	24	0.2	15.80	25	0	0	10.80	1.45	23
28	17	0.26	13.28	16	0	0	11.78	0.86	15
29	13	3.44	2.37	16	0	0	4.01	0.70	11
30	15	0.23	13.09	20	0	0	6.85	1.05	20
31	20	1.19	2.98	9	0	0	4.16	0.35	15
32	16	0.31	11.28	10	0	0	7.06	1.02	9
33	15	0.01	13.81	13	0.001	0.01	11.63	1.50	19
34	11	0	5.20	14	0	0	2.96	0.76	10
35	19	0.77	10.86	13	0	0	10.04	0.61	17
36	22	1.94	16.27	29	0	0	13.43	1.61	25
37	19	2.48	7.35	16	0	0	9.72	1.19	15
38	29	0.22	18.92	31	0.007	0.02	17.90	1.61	31
39	36	3.54	10.08	26	0	0	9.70	1.38	19
40	30	1.88	14.23	25	0.003	0.01	17.71	1.05	23
41	16	0	10.28	14	0	0	7.11	1.15	17
42	22	0	10.17	11	0	0	7.36	1.20	10
43	1	1.04	0.00	4	0	0	2.13	0.22	3
44	28	1.63	12.09	21	0	0	13.34	1.45	26
45	21	0	12.39	14	0	0	10.62	1.28	15
46	25	2.39	15.02	18	0	0	8.69	1.31	16
47	21	0.09	14.52	6	0	0	11.04	1.45	9
48	19	5.18	11.62	28	0	0	11.30	1.49	19
49	26	0.06	14.29	27	0	0	9.24	1.35	20

Table 4.9 – *Continued*

50	16	1.32	15.54	13	0	0	11.70	1.50	12
51	30	6.91	12.56	24	0.874	0.28	20.11	1.28	22
52	6	0.77	0.93	6	0	0	2.37	0.35	8
53	27	2.83	15.65	22	0.096	0.04	20.94	0.48	20
54	40	3.13	11.87	29	0	0	10.28	1.42	23
55	26	4.7	10.20	21	0	0	14.88	1.36	18
56	27	0	0.00	2	0	0	7.13	0.96	13
57	23	2.57	5.43	8	0	0	4.84	0.84	9
58	20	0	10.76	17	0	0	10.23	1.29	16
59	26	0	9.36	30	0	0	10.86	1.31	15
60	12	4.33	14.61	16	0	0	6.59	0.53	9
61	16	2.09	9.77	16	0.006	0.02	13.78	1.26	15
62	3	0.77	0.00	2	0	0	1.44	0.28	3
63	34	2.53	13.31	33	0	0	13.16	1.37	24
64	42	2.33	12.79	39	0.004	0.02	12.21	1.53	36
65	27	3.18	11.94	23	0	0	14.99	1.18	23
66	27	3.3	18.25	16	0	0	12.58	1.57	21
67	33	3.85	15.60	20	0	0	15.89	1.71	18
68	30	1.47	17.12	19	0	0	12.65	1.58	14
69	18	0	10.29	20	0	0	6.38	1.11	26
70	29	2.46	17.38	27	0	0	15.71	1.40	23
71	18	2.08	5.30	15	0	0	6.10	1.03	15
72	21	0.01	11.64	11	0	0	8.26	1.26	5
73	22	0.02	13.26	19	0	0	10.63	1.17	9
74	25	0.96	6.66	20	0	0	6.54	1.12	19
75	17	0.33	3.35	17	0	0	2.79	0.66	20
76	36	2.2	12.23	16	0	0	12.71	1.56	8
77	28	5.59	13.06	28	0	0	16.58	1.31	28
78	5	0.67	0.00	3	0	0	0.80	0.28	2
79	46	1.58	13.12	18	0.222	0.18	15.65	1.29	16
80	12	2.34	10.09	18	0	0	4.73	0.44	5
81	24	3.35	10.41	18	0	0	15.39	1.50	21
82	24	0	10.62	21	0	0	10.03	1.37	34
83	6	1.56	1.33	2	0	0	1.44	0.18	2
84	43	1.37	13.48	19	0.002	0.01	12.13	1.49	18
85	27	0	11.35	16	0	0	8.48	1.29	19
86	22	1.98	10.19	18	0	0	6.64	0.46	15
87	15	0.21	14.58	0	0.023	0.06	13.68	1.57	8
88	33	1.99	12.87	25	0	0	13.91	1.57	34
89	15	0.17	6.51	14	0	0	4.75	0.90	13

4.4.3. Re-optimization result of PDA Model

Table 4.10 illustrates the results for the PDA outcome. There are 9 patients who have higher final outcomes than the original dataset. In Appendix C, we can see some treatments are scarcely used. They are RxGr8, RxGr7, ProcGr4 at stage 1 and RxGr3 at stage 2.

Table 4.10 Comparison of PDA Model: Treatment utilization (TU), SDP re-optimization outcome (SDP), and Original data outcome (Orig).

	Pre	MidPDA			PostPDA				
	PDA	TU	(Reopti)	(Origi)	TU	StD	SDP	StD	(Orig.)
1	10	2.7	1.271	7	4.3	0.74	1.24	0.76	8
2	10	1.4	0.429	8	4.6	0.61	0.39	0.33	8
3	7	0.3	1.452	5	1.8	1.00	1.64	0.44	3
4	9	2	2.806	4	5.7	1.32	2.33	0.77	2
5	8	1.1	1.483	8	4.6	1.15	1.65	0.66	8
6	8	3.7	1.214	5	7.1	0.80	3.22	0.79	1
7	2	6.4	1.614	4	5.8	0.79	1.68	0.74	3
8	9	2.8	1.464	9	5.2	0.73	0.79	0.53	8
9	7	0.9	2.011	6	2.7	1.18	1.36	0.45	5
10	9	0.5	1.428	6	0.9	0.43	1.10	0.52	5
11	7	0.1	0.210	8	5.4	0.98	1.44	0.54	7
12	9	1.5	0.477	8	6.2	0.86	1.97	0.67	8
13	8	0.8	2.307	6	4.3	1.39	2.46	1.01	6
14	7	5.3	1.036	4	1.6	0.92	1.37	0.31	3
15	9	0.4	1.275	5	4.6	0.70	0.65	0.45	6
16	9	1.8	0.913	7	4.3	0.60	0.32	0.30	5
17	6	6.7	3.301	5	6.4	1.85	3.57	0.59	4
18	8	3.1	2.409	7	6.1	1.02	2.20	0.79	7
19	7	3.9	1.217	5	7.2	0.58	2.89	0.77	4
20	7	0.6	0.947	3	1.6	0.97	0.91	0.40	6
21	10	3.1	1.739	3	2.4	1.09	1.11	0.60	3
22	7	4.6	0.415	4	5.7	0.78	1.52	0.73	4
23	2	1	0.659	2	2	0.57	2.51	0.35	0
24	7	3.3	0.599	6	0.6	0.32	0.67	0.22	4
25	7	1.1	2.477	2	2.8	1.38	2.37	0.53	2
26	9	3.6	1.916	8	5.3	1.38	2.29	0.79	7
27	8	2.4	1.428	6	5.6	0.97	1.75	0.76	1
28	6	0.9	0.953	2	0.7	0.30	0.80	0.43	4
29	9	0.3	0.300	5	2.2	0.87	0.71	0.34	5

Table 4.10 – *Continued*

30	8	3.8	1.936	4	5	1.04	1.55	0.72	4
31	3	1.2	1.615	3	1.4	0.49	1.73	0.35	5
32	5	0.8	0.612	5	1	1.14	1.47	0.49	1
33	6	2.8	1.993	7	1.3	1.01	1.69	0.71	8
34	8	0.5	0.397	3	4.2	0.66	0.89	0.49	3
35	5	3.8	3.249	3	0.2	0.76	4.35	0.62	4
36	6	0.7	1.028	10	4.2	1.52	2.22	0.63	8
37	5	1.2	1.796	7	2.4	1.23	2.03	0.45	5
38	8	0.7	1.132	7	3.2	1.46	2.08	0.53	7
39	9	1.6	0.251	4	4.1	0.62	0.68	0.45	3
40	7	1.5	2.266	7	1	0.36	1.21	0.50	3
41	5	3.2	1.855	5	6.6	2.01	5.96	0.85	3
42	8	0.4	0.373	2	4.1	0.72	0.94	0.51	5
43	4	1	0.334	3	0.2	0.60	1.71	0.28	3
44	8	0.6	0.508	2	1	0.36	1.21	0.44	4
45	5	0.3	1.427	2	2.4	1.25	1.95	0.49	2
46	8	0.4	1.562	3	5.4	0.92	1.53	0.73	6
47	7	0.7	1.458	0	1.1	1.17	1.35	0.53	0
48	6	0.8	0.600	4	2.9	1.34	1.77	0.46	7
49	10	0.4	0.587	7	6	0.60	1.47	0.74	6
50	3	0.7	1.643	5	3.4	1.40	1.83	0.58	2
51	8	2.7	2.204	8	5.7	0.75	1.36	0.70	5
52	5	1.3	0.983	3	1	0.56	0.96	0.33	2
53	4	2	1.953	4	1.1	0.33	1.35	0.47	2
54	8	1.9	0.023	6	0.4	0.56	0.48	0.36	8
55	7	2.5	3.250	5	2.2	1.77	2.99	0.73	3
56	7	0.1	0.206	1	0.3	0.44	0.05	0.23	2
57	8	1.9	2.223	1	2.6	0.84	0.57	0.39	2
58	7	2.1	2.388	6	3.5	1.59	2.54	0.54	4
59	7	0.8	2.147	7	3.1	1.47	2.36	0.55	7
60	8	7.9	2.281	4	5.1	1.20	1.95	0.70	4
61	6	1.6	2.305	4	0.8	0.36	0.93	0.51	3
62	6	0.9	1.317	5	1.2	0.76	1.01	0.34	2
63	7	3.4	1.346	7	2.8	1.21	1.35	0.51	2
64	10	2.5	0.675	10	4.9	0.67	0.73	0.49	7
65	8	2	1.115	7	0	0.12	2.37	0.63	6
66	6	6.4	2.256	7	8.3	1.27	3.55	0.65	6
67	9	3.1	1.955	8	1.8	1.30	2.34	0.77	7
68	8	4.9	1.530	7	1.2	0.59	1.44	0.71	4
69	8	0.2	0.285	4	2.6	0.80	0.67	0.36	5

Table 4.10 – *Continued*

70	7	3.7	1.685	7	4.8	1.97	4.12	0.54	7
71	9	0	0.057	5	0.8	0.43	0.84	0.41	5
72	8	0.8	1.337	2	3.4	1.04	1.11	0.52	2
73	6	0.6	0.701	3	1.6	0.90	1.48	0.40	5
74	9	3.9	2.247	6	6.3	1.70	3.87	0.77	4
75	10	0.8	0.841	7	3.3	0.97	1.09	0.48	8
76	7	2.2	0.808	6	1.3	1.09	1.70	0.70	4
77	8	2.1	2.568	5	5.4	1.50	2.51	0.79	8
78	10	0	0.004	1	4.2	0.52	0.97	0.49	2
79	8	1.9	2.204	6	4	1.62	2.40	0.65	4
80	7	1	0.711	6	1.9	1.02	1.61	0.36	6
81	7	1.9	1.126	3	5.1	0.94	3.32	0.30	7
82	8	0.2	1.215	9	3.8	1.46	2.03	0.61	8
83	6	3.6	1.143	2	3	1.31	1.72	0.45	3
84	7	1.9	1.619	6	4.1	1.42	1.99	0.65	6
85	9	0.3	0.609	7	4.1	0.95	1.23	0.57	8
86	9	2	1.491	7	0.4	0.30	0.35	0.49	3
87	6	1.7	2.609	2	6.3	0.69	1.95	0.83	2
88	6	3.2	2.250	6	1.8	1.50	2.40	0.74	5
89	8	3.1	2.026	7	4.3	1.60	2.44	0.64	6

4.4.4. Summary of Re-optimization Result

Overall, the SDP Re-optimization yields better outcomes than were seen in the original dataset. Table 4.4 summaries the comparison for each outcome measurement. The first column is the name of outcome measurement. The second column gives the number of treatment variables that were selected by the regression modeling in section 4.1,where the treatment variables in the second stage are given in parentheses. The SDP optimized outcomes are evaluated two ways, by comparing to the normal/low range and by comparing to the outcomes in the original data, The third column shows how many of the 89 patients had a final SDP optimized outcome greater than the normal range in BDI and OSW cases or low range in PDA. Please see section 3.1.9 for the definition of normal and low ranges for each outcome measurement. The numbers in parentheses are the corresponding counts from original dataset.

The last column shows the numbers of patients having higher outcome values than the original dataset. The first sub column of the last column shows the number of patients whose final optimized outcomes are greater than original dataset but within the normal range. In other words, these patients have achieved an outcome that does not require treatment. However, those patients having scores greater than the original dataset and also greater than the normal or low ranges in the second sub column are our main concern because these are the patients for whom the SDP re-optimization was unsuccessful in identifying a better treatment regime. In the next section, an overall comparison analysis for two groups, SDP re-optimization result and original dataset by using a t-test and estimating an odds ratio present.

Table 4.11 Summary of SDP final Optimized Outcome

	# Treatments: 1^{st} (2^{nd}) stage	Final Optimized Outcome (Original) > Normal/Low	Final Optimized Outcome > Original	
			Normal	> Normal
BDI	13 (6)	1 (28)	18	0
OSW	10 (3)	46 (64)	15	8
PDA	12 (4)	8 (58)	6	3

4.5 T-test and Chi-square Test Results

Student's t-test and an odds ratio are employed here to give us an overall comparison between the SDP re-optimization outcomes and the outcomes in the original dataset. Since patients that have a pre-evaluation outcome within the normal/low range do not require treatment, for each outcome measure, these “normal” patients are excluded from the comparison. Hence, the comparison focuses on the impact of the SDP optimization for those patients that required treatment. The included observations were 56 in BDI case, 79 in OSW case and 85 in PDA case. The results for each of the three outcome measurements are listed in the three tables below. Each table contains a Student's t-test and an odds ratio estimated from a 2×2 contingency table.

A one-sided paired Student's t-test is used here to test whether the mean of the SDP outcomes is smaller than the mean of original outcomes. The null hypothesis for this test states that there is no difference between the means of two groups; the alternative hypothesis is that the mean of the SDP group is lower than the mean of the original dataset. As can be seen in the results in below, the null hypothesis is rejected in all cases at a significance level of 0.01. In other words, we can conclude that the mean outcome from SDP re-optimization is lower than the mean outcome from the original dataset.

To calculate the odds ratio, we organize counts from optimized data and original data in categories according to a 2×2 contingency table. It should be noted that the optimized data is simulated from SDP re-optimization and is not actual data. In our contingency table, the first column describes where the data source; the second column shows the counts of final post outcome in the normal range; the third column gives the counts greater than the normal range; the last column shows the proportions of two dataset in normal ranges. Then, odds and odds ratio can be calculated. From odds ratio, we can interpret how much more likely an outcome will be in the normal range for the SDP optimized outcome vs. the original data. Specifically, the SDP-optimized PostBDI is estimated to be 44.35 times more likely to achieve a normal level (10 of lower), the SDP-optimized PostOSW is estimated to be 2.82 times more likely to achieve a normal level (10 of lower), and the SDP-optimized PostPDA is estimated to be 19.59 times more likely to achieve a low level (3 or lower).

Table 4.12 T-test and Odds ratio results for PostBDI

PostBDI (Pre>10) n=56		
T-test (α=0.05)		
	SDP	Original
Average	3.4	11.821
# replication	56	56
df	55	55
Sum of square	304	4886.2
Variance	5.53	88.84
SD	2.35	9.426
Effect size	-8.42	
H0: μ (SDP) = μ (Orig) H1: μ (SDP) < μ (Orig)		
P-value(1-tailed)	2E-10	
Reject H0, the mean of SDP is smaller than original.		

2×2 Contingency Table

Final Post Outcome	# of Normal	# > Normal (10)	Pro. Of Normal
A: Optimized data	55	1	0.98
B: Original data	31	25	0.55

Odds for A (r1)	55	Odds ratio	
Odds for B (r2)	1.24	(r1/r2)	44.35

Table 4.13 T-test and Odds ratio results for PostOSW

PostOSW (Pre>10) n=79		
T-test (α=0.05)		
	SDP	Original
Average	10.99	17.7848
# replication	79	79
df	78	78
Sum of square	1491	4275.34
Variance	19.11	54.8121
SD	4.372	7.40352
Effect size	-6.80	
H0: μ (SDP) = μ (Orig) H1: μ (SDP) < μ (Orig)		
P-value(1-tailed)	8.5E-11	
Reject H0, the mean of SDP is smaller than original.		

2×2 Contingency Table

Final Post Outcome	# of Normal	# > Normal (10)	Pro. Of Normal
A: Optimized data	33	46	0.42
B: Original data	16	63	0.20

Odds for A (r1)	0.72	Odds ratio	
Odds for B (r2)	0.25	(r1/r2)	2.82

Table 4.14 T-test and Odds ratio results for PostPDA

PostPDA (Pre>3) n=85

T-test (α=0.05)

	SDP	Original
Average	1.73	4.706
# replication	85	85
df	84	84
Sum of square	84.71	393.647
Variance	1.01	4.686
SD	1.004	2.165
Effect size	-2.98	
H0: μ (SDP) = μ (Orig) H1: μ (SDP) < μ (Orig)		
P-value(1-tailed)	2E-10	
Reject H0, the mean of SDP is smaller than original.		

2×2 Contingency Table

Final Post Outcome	# of Normal	# > Normal (10)	Pro. Of Normal
A: Optimized data	77	8	0.91
B: Original data	28	57	0.33

Odds for A (r1)	9.63	Odds ratio (r1/r2)	19.59
Odds for B (r2)	0.49		

CHAPTER 5

DISCUSSION AND FUTURE RESEARCH

5.1 Discussion

In this research, statistics and optimization techniques are employed to develop a computationally-tractable SDP solution for adaptive pain management. Generally speaking, the simulation results of the forward on-line re-optimization demonstrate the strong potential for improving patients' pain outcomes, particularly BDI and PDA.Most patients have lower outcome pain values than the original dataset, where the SDP-optimized PostBDI was estimated to be over 44 times more likely to achieve a normal level (10 of lower), and the SDP-optimized PostPDA was estimated to be over 19 times more likely to achieve a low level (3 or lower). Only one patient in the BDI case has a lower final outcome, 11 in the OSW case, and 9 in the PDA case. For the one in the BDI case, the PostBDI is around 10, which is considered to be normal; among the 11 patients in the OSW case, there are only five patients whose final outcome was over 10; in the PDA case, only 3 patients' outcomes are above 3, and the others are around 1 or 2.

From all three cases (BDI, OSW, PDA), it seems like some used treatments in the 1^{st} stage are also applied in the 2^{nd} stage. In other words, the treatments in the 2^{nd} stage have been applied in the 1^{st} stage, and there are no new treatments that are identified as important variables. With the PDA case as an example, its treatments in the stage 2 are RxGr3, RxGr4, RxGr5 and ProdGr4. They all have been selected in the stage 1 as well. The other two cases show the same relation as well. The three final outcome models all have the state transition function of $NumGr_1$. The variables not identified as important variables are $NumPsy_1$, Status, PhyDx4, PhyDx9, PhyDx11, PhyDx14, $RxGr1_2$, $RxGr6_2$, $RxGr8_2$, $ProcGr1_2$ and $ProcGr10_2$.

Nevertheless, one thing catching our attention is some treatments are hardly used as we see in Appendix B for the usage of treatment options. Almost no treatment is used in the stage 2 of BDI case since all outcome values are already low in stage 1. Therefore, no treatment action is taken after that for all patients. Nevertheless, it does not sound what happen in the real world. In the mid-evaluation of BDI, $ProdGr11_1$ (u13) is never applied; only 4 patients used $RxGr8_1$ (u6); $ProdGr10_1$ (u13) and $RxGr1_1$ (u12) are applied 5 times. In the mid-evaluation of OSW, $RxGr4_1$ (u10) is applied only 6 times; in the post-evaluation of OSW, $ProdGr9_2$ (u1) is applied only 2 times. In the mid-stage of PDA, $ProdGr4_1$ (u12) is never used; $RxGr8_1$ (u4) and $RxGr7_1$ (u11) are only used once; $ProdGr9_1$ (u3) is only used 6 times. In the post-evaluation of PDA, $RxGr3_2$ (u1) is only applied 3 times Additionally, we found out that there are more treatments options in mid-stage for all three outcome models. In BDI case, there are 13 treatments in the 1st stage and 6 treatments in 2nd stage; in OSW case, there are 10 treatments in the 1st stage and 3 treatments in the 2nd stage; in PDA case, there are 12 treatments in the 1 stage and 4 in the 2nd stage.

In this research, we identified important variables for each stage and also reduced the number of variables. Moreover, we optimized the selection of treatment options for each stage. The simulation of the re-optimization shows very promising results. In practice, this prototype could be employed to recommended treatment groups from which doctors can assign specific medications or procedures.

5.2 Future Research

This research developed a prototype for a dynamic decision support system for pain management. Many tasks still r need to be explored. First, more data are needed. In this research, the clean dataset only has 89 patients. Second, limitations on treatments or combinations of treatments are not applied due to lack of information. For instance, if we use treatment A, we cannot use treatment B since it may cause some conflicts or detrimental

interactions. Once we receive this kind of knowledge from pain management experts, we can easily implement that information as constraints in our SDP optimization model.

Third, the data are composed of a mix of categorical and numerical variables, where the categorical variables were primarily binary (e.g., Procedure = 1 if applied, and 0 if not), although some had more categories (e.g. pain type, pain status). The prototype in this dissertation treats all variables as continuous. A Tree-MARS had been applied previously to properly address the mix of variable types (Sahu et al. 2009); however, it was found that the regression model yielded better predictions. Proper handling of a mix of categorical and continuous state variables in SDP is an area of future research. We may use Tree-MARS to replace the way we approximate the future value function, as well as state transitions.

The final task that needs to be addressed is the handling of the multiple objectives. In this research we have three different outcome measures for each patient; right now we optimized the decision values for each outcome measure individually; however, in reality, we want to simultaneously optimize the treatment decision variables over all three outcome measure, but there may be a tradeoff between outcome measures or treatments.

In this research, we presented a two-stage adaptive framework for pain management and discussed details on modeling. This prototype successfully demonstrated the potential for dynamically optimizing pain management treatment. The SDP solution method was computationally-tractable, requiring only about 10 minutes of run time. The on-line re-optimization required about 3 hours to conduct 1000 simulation runs for all 89 patients, or about 0.12 seconds per patient per simulation run.

APPENDIX A

SAS OUTPUT FOR OUTCOME MODELS REGRESSION ASSUMPTIONS

Preliminary Model 1 of MidBDI

Confirm P-Model 1 Alpha=0.1

Dependent Variable: mid_bdi

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	8	6240.46634	780.05829	29.52	<.0001
Error	82	2166.83037	26.42476		
Corrected Total	90	8407.29670			

Root MSE	5.14050	R-Square	0.7423
Dependent Mean	10.91209	Adj R-Sq	0.7171
Coeff Var	47.10833		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	3.97914	3.71679	1.07	0.2875	0
pre_bdi	1	0.70746	0.05731	12.34	<.0001	1.11145
litigat	1	3.83404	1.65827	2.31	0.0233	1.15957
phydxoth	1	4.49362	1.63884	2.74	0.0075	1.13255
sghxot1	1	-3.72264	1.40280	-2.65	0.0096	1.08186
pastdx11	1	2.27802	0.94348	2.41	0.0180	1.12462
status	1	-2.48089	1.17337	-2.11	0.0375	1.06380
D_2G3	1	1.19989	0.55305	2.17	0.0329	1.06438
Pr_2G10	1	2.18885	1.23194	1.78	0.0793	1.04139

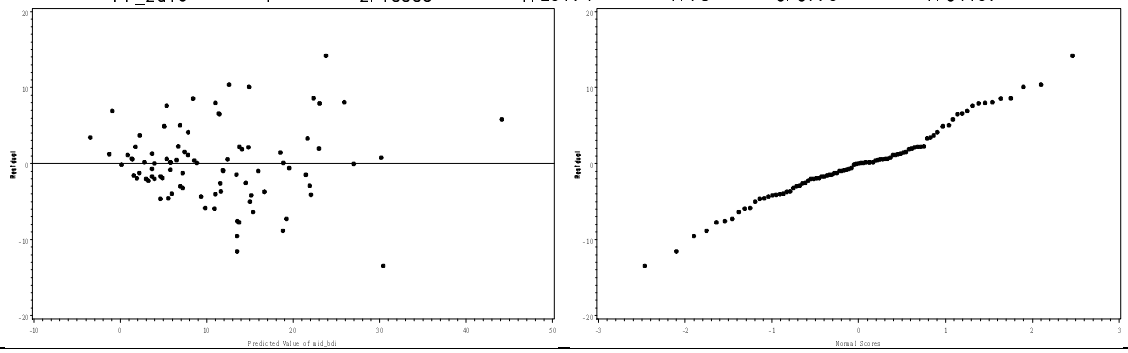


Figure A.1 Preliminary Model 1 of MidBDI

✓ Preliminary Model 2 of MidBDI - SqrtY

Confirm P-Model 2 Alpha=0.1

Dependent Variable: SqrtY

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	147.36883	24.56147	35.81	<.0001
Error	84	57.62081	0.68596		
Corrected Total	90	204.98964			

Root MSE	0.82823	R-Square	0.7189
Dependent Mean	2.94270	Adj R-Sq	0.6988
Coeff Var	28.14523		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.83325	0.21506	3.87	0.0002	0
pre_bdi	1	0.12309	0.00894	13.76	<.0001	1.04276
phydxoth	1	0.62941	0.25213	2.50	0.0145	1.03260
Pr_2G4	1	-0.48820	0.22791	-2.14	0.0351	1.04851
children	1	0.12929	0.05619	2.30	0.0239	1.07537
phydx14	1	-0.77563	0.33350	-2.33	0.0224	1.04769
D_2G3	1	0.18160	0.08690	2.09	0.0397	1.01237

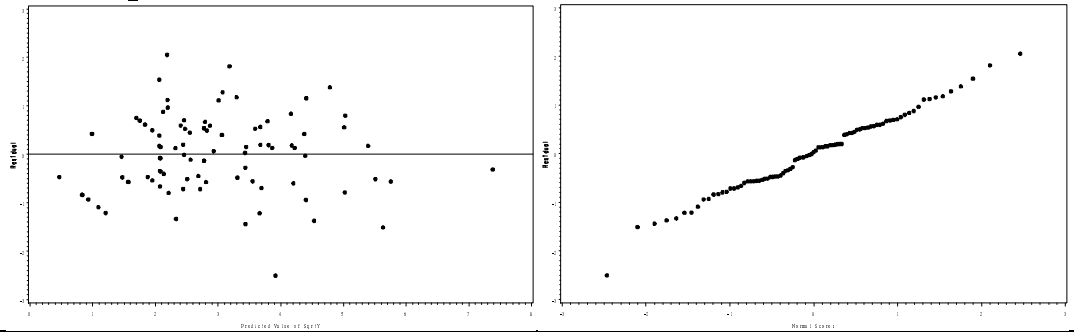


Figure A.2 Preliminary Model 2 of MidBDI

Model A of MidBDI:

SqrtY = ALL state and decision variables and STD interaction terms (All Dec.and Selected Sta.V.from SqrtY)

Confirm for Model A

Dependent Variable: SqrtY

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	154.63794	25.77299	43.00	<.0001
Error	84	50.35170	0.59942		
Corrected Total	90	204.98964			

Root MSE	0.77423	R-Square	0.7544
Dependent Mean	2.94270	Adj R-Sq	0.7368
Coeff Var	26.31008		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.40753	0.19701	7.14	<.0001	0
pre_bdi	1	0.11265	0.00836	13.47	<.0001	1.04360
std2G3_stdx46	1	-0.50204	0.11674	-4.30	<.0001	1.06228
std2G5_stdx30	1	-0.65185	0.20124	-3.24	0.0017	1.03816
stp2G4_stdx45	1	0.36611	0.13109	2.79	0.0065	1.01444
phydx3	1	-0.55265	0.26238	-2.11	0.0382	1.02225
stp2G10_stdx30	1	-0.26576	0.13556	-1.96	0.0533	1.08269

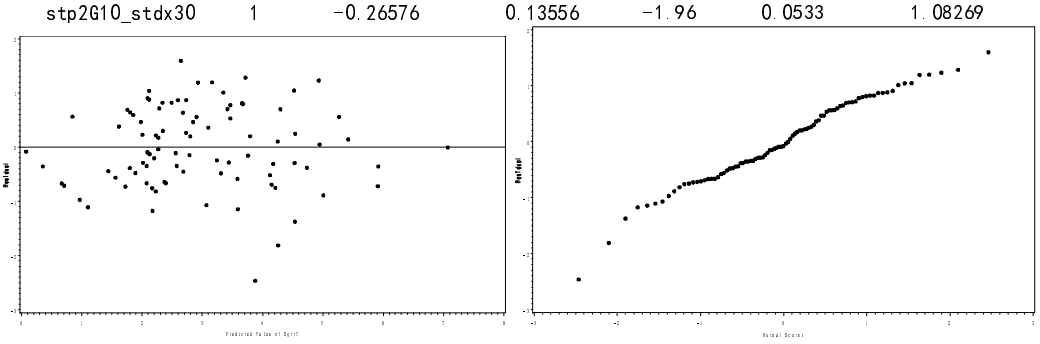


Figure A.3 Model A of MidBDI

Model B of MidBDI:

SqrtY = Selected state and decision variables and STD interaction terms (All Dec.and Selected Sta.V.from SqrtY)

Confirm for Model B

Dependent Variable: SqrtY

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	8	160.28978	20.03622	36.76	<.0001
Error	82	44.69985	0.54512		
Corrected Total	90	204.98964			

Root MSE	0.73832	R-Square	0.7819
Dependent Mean	2.94270	Adj R-Sq	0.7607
Coeff Var	25.09001		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.25913	0.20826	6.05	<.0001	0
pre_bdi	1	0.12400	0.00879	14.11	<.0001	1.26622
std2G3_stdx46	1	-0.55296	0.13355	-4.14	<.0001	1.52877
stp2G4_stdx45	1	0.30588	0.12776	2.39	0.0189	1.05948
stp2G10_stdx30	1	-0.27172	0.13238	-2.05	0.0433	1.13535
std2G8_stdx30	1	-0.63361	0.16196	-3.91	0.0002	1.10345
std2G5_stdx46	1	-0.46604	0.16257	-2.87	0.0053	1.56501
std2G7_stdx46	1	0.39923	0.15110	2.64	0.0099	1.90398
std2G2_stdx6	1	0.41947	0.20205	2.08	0.0410	1.22969

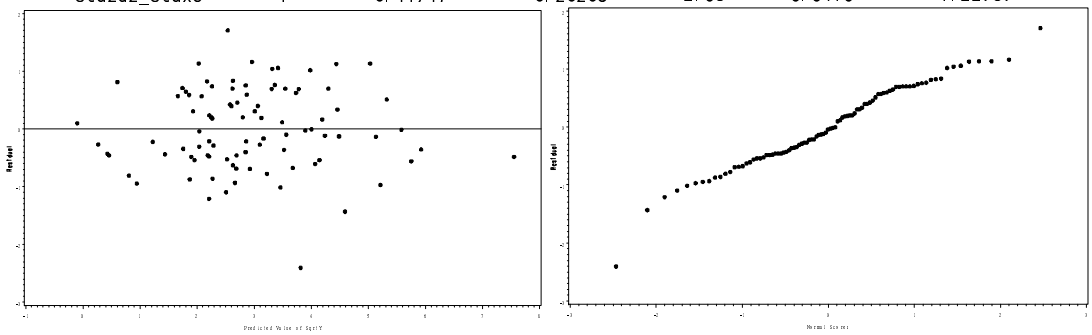


Figure A.4 Model A of MidBDI

Model C-1 of MidBDI:

SqrtY = ALL state and decision variables and STD interaction terms (from All Dec.and Sta.V.)

Confirm Model C Alpha=0.05

Dependent Variable: SqrtY

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	185.09854	10.88815	39.96	<.0001
Error	73	19.89110	0.27248		
Corrected Total	90	204.98964			

Root MSE	0.52200	R-Square	0.9030
Dependent Mean	2.94270	Adj R-Sq	0.8804
Coeff Var	17.73874		

Parameter Variable	DF	Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.45940	0.26537	1.73	0.0877	0
pre_bdi	1	0.12446	0.00693	17.97	<.0001	1.57439
std2G3_stdx46	1	-0.37903	0.08402	-4.51	<.0001	1.21053
std2G5_stdx30	1	-1.05722	0.17452	-6.06	<.0001	1.71768
stp2G9_stdx37	1	-0.28938	0.06447	-4.49	<.0001	1.10621
stp2G4_stdx25	1	0.50365	0.12587	4.00	0.0001	1.25048
std2G2_stdx40	1	0.34580	0.08259	4.19	<.0001	1.25420
std2G8_stdx48	1	-0.28842	0.07228	-3.99	0.0002	1.23882
std2G5_stdx33	1	0.69986	0.14893	4.70	<.0001	2.30030
S_G2	1	0.97049	0.25068	3.87	0.0002	2.05274
std2G4_stdx35	1	0.74321	0.16923	4.39	<.0001	7.53318
std2G6_stdx32	1	0.31357	0.08551	3.67	0.0005	1.28166
std2G6_stdx41	1	-0.27054	0.07788	-3.47	0.0009	1.57168
std2G5_stdx41	1	0.43488	0.12211	3.56	0.0007	1.73480
stp2G1_stdx31	1	-0.34074	0.08667	-3.93	0.0002	1.26671
std2G7_stdx4	1	0.53851	0.21804	2.47	0.0159	1.47045
phydx9	1	1.26940	0.37449	3.39	0.0011	1.49316
std2G4_stdx43	1	-0.39737	0.15571	-2.55	0.0128	7.26125

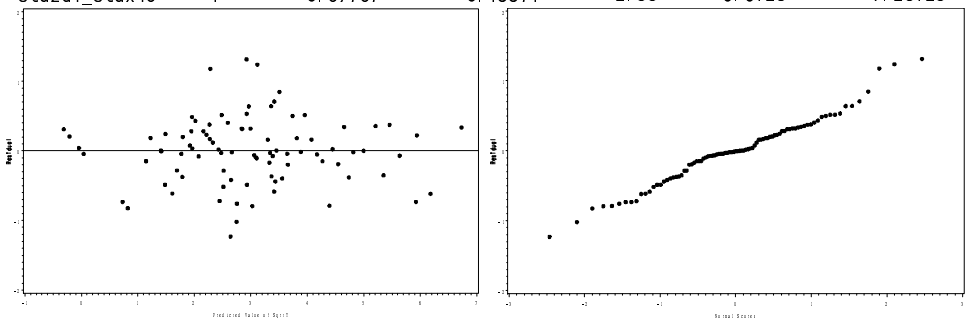


Figure A.5 Model C–1 of MidBDI

✓ Mid_BDI - Model C-2 with Alpha=0.05 after taking off " std2G4_stdx43 "
The VIF seems okay now.

Dependent Variable: SqrtY

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	186.09729	10.33874	39.40	<.0001
Error	72	18.89235	0.26239		
Corrected Total	90	204.98964			

Root MSE	0.51224	R-Square	0.9078
Dependent Mean	2.94270	Adj R-Sq	0.8848
Coeff Var	17.40730		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-0.09475	0.27009	-0.35	0.7268	0
pre_bdi	1	0.13464	0.00676	19.92	<.0001	1.55615
std2G3_stdx46	1	-0.40565	0.08342	-4.86	<.0001	1.23921
std2G5_stdx30	1	-1.09189	0.17313	-6.31	<.0001	1.75531
stp2G9_stdx37	1	-0.23998	0.06620	-3.63	0.0005	1.21124
stp2G4_stdx25	1	0.45952	0.13323	3.45	0.0009	1.45490
std2G2_stdx40	1	0.37461	0.08103	4.62	<.0001	1.25361
std2G8_stdx48	1	-0.30751	0.07100	-4.33	<.0001	1.24132
std2G5_stdx33	1	0.78226	0.14358	5.45	<.0001	2.22019
S_G2	1	1.16761	0.23336	5.00	<.0001	1.84730
std2G4_stdx35	1	0.28569	0.07524	3.80	0.0003	1.54631
std2G6_stdx32	1	0.34820	0.08362	4.16	<.0001	1.27265
std2G6_stdx41	1	-0.30993	0.07352	-4.22	<.0001	1.45474
std2G5_stdx41	1	0.49873	0.12128	4.11	0.0001	1.77717
stp2G1_stdx31	1	-0.30379	0.08273	-3.67	0.0005	1.19855
std2G7_stdx4	1	0.60802	0.21424	2.84	0.0059	1.47414
phydx9	1	0.96813	0.33060	2.93	0.0046	1.20840
stp2G10_stdx51	1	-0.18238	0.06856	-2.66	0.0096	1.41590
stp2G4_stdx35	1	0.33611	0.14012	2.40	0.0190	1.32216

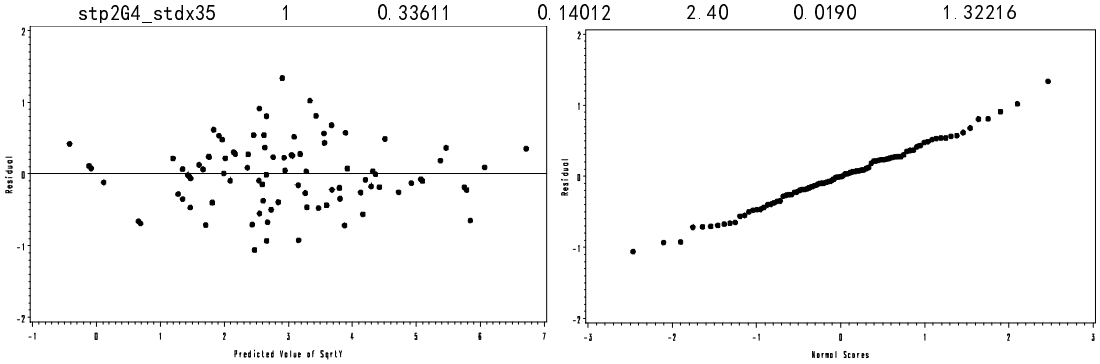


Figure A.6 Model C–2 of MidBDI

✓ Preliminary Model 1 of MidOSW

Confirm Stepwise Results for P-Model Alpha=0.1

Dependent Variable: mid_osw

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	10	4590.40549	459.04055	18.52	<.0001
Error	80	1983.19891	24.78999		
Corrected Total	90	6573.60440			

Root MSE	4.97895	R-Square	0.6983
Dependent Mean	17.78022	Adj R-Sq	0.6606
Coeff Var	28.00277		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-11.89526	4.12599	-2.88	0.0051	0
pre_osw	1	0.41652	0.06744	6.18	<.0001	1.46956
pre_bdi	1	0.18842	0.06240	3.02	0.0034	1.40461
S_G2	1	5.89577	1.73535	3.40	0.0011	1.08128
phydx3	1	-5.11249	1.75920	-2.91	0.0047	1.11121
Do_2G8	1	9.52919	2.69478	3.54	0.0007	1.12023
status	1	3.84223	1.17523	3.27	0.0016	1.13755
pre_pda	1	0.76775	0.34708	2.21	0.0298	1.32242
Do_2G7	1	2.33810	0.97777	2.39	0.0191	1.31715
sghxot1	1	-2.89756	1.33767	-2.17	0.0333	1.04861
Do_2G3	1	0.95918	0.53991	1.78	0.0794	1.08129

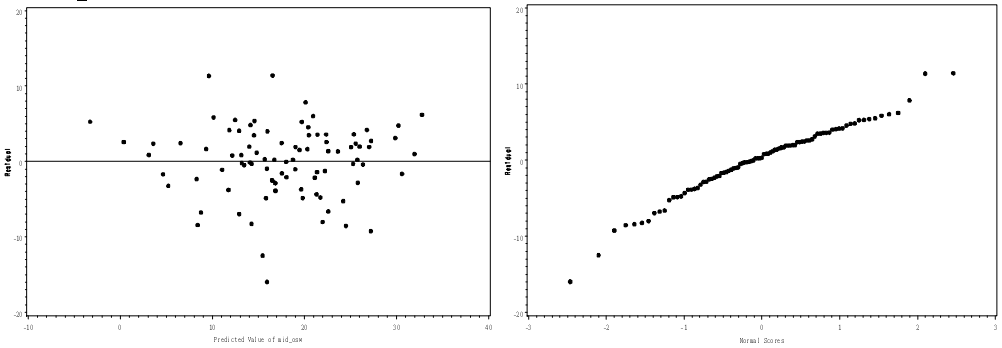


Figure A.7 Preliminary Model 1 of MidOSW

Preliminary Model 2 of MidOSW - SqrtY

Confirm P-Model 2 Alpha=0.1

Dependent Variable: SqrtY

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	78.52604	11.21801	16.07	<.0001
Error	83	57.95215	0.69822		
Corrected Total	90	136.47819			

Root MSE	0.83559	R-Square	0.5754
Dependent Mean	4.03491	Adj R-Sq	0.5396
Coeff Var	20.70916		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.76526	0.39505	4.47	<.0001	0
pre_osw	1	0.05935	0.01123	5.28	<.0001	1.44742
sghxot2	1	-0.18707	0.07493	-2.50	0.0145	1.03733
pre_bdi	1	0.02550	0.00949	2.69	0.0087	1.15325
S_G2	1	0.64350	0.28823	2.23	0.0283	1.05909
Pr_2G4	1	-0.44146	0.22766	-1.94	0.0559	1.02779
phydx3	1	-0.66819	0.29429	-2.27	0.0258	1.10409
pre_pda	1	0.09833	0.05736	1.71	0.0902	1.28256

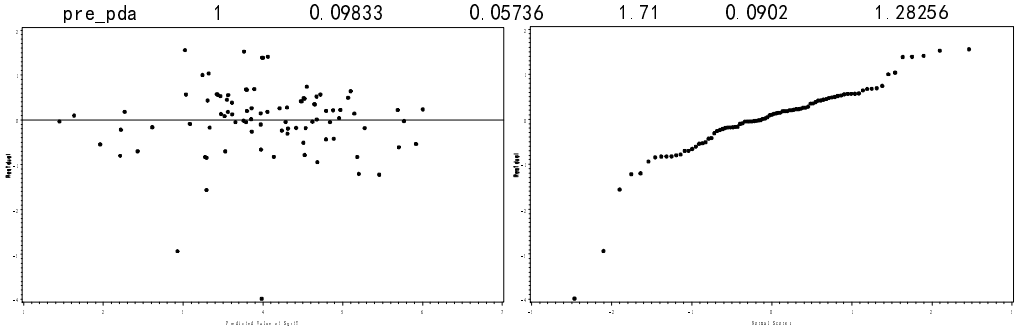


Figure A.8 Preliminary Model 2 of MidOSW

Model A of MidOSW:

mid_osw = ALL state and decision variables and STD interaction terms (All Dec. and Selected Sta. V. from mid_osw)

Confirm for Model A

Dependent Variable: mid_osw

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	5016.71975	456.06543	23.14	<.0001
Error	79	1556.88465	19.70740		
Corrected Total	90	6573.60440			

Root MSE	4.43930	R-Square	0.7632
Dependent Mean	17.78022	Adj R-Sq	0.7302
Coeff Var	24.96764		

Parameter Estimates

Parameter Variable	DF	Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	17.80485	1.16988	15.22	<.0001	0
stp2G1_stdx7	1	-10.99552	1.54437	-7.12	<.0001	1.49049
std2G8_stdx6	1	-6.06546	1.27551	-4.76	<.0001	1.51439
std2G7_stdx33	1	-2.54491	0.69238	-3.68	0.0004	1.08565
sghxot2	1	-1.21780	0.42195	-2.89	0.0050	1.16532
stp2G9_stdx5	1	3.55279	1.02690	3.46	0.0009	1.13281
stp2G4_stdx37	1	2.17385	0.75865	2.87	0.0053	1.11298
stp2G1_stdx35	1	3.20533	1.07326	2.99	0.0038	1.10147
std2G4_stdx6	1	2.36376	0.99184	2.38	0.0196	1.32727
std2G2_stdx37	1	-1.85803	0.73437	-2.53	0.0134	1.20289
std2G5_stdx7	1	-5.39166	2.09133	-2.58	0.0118	1.76575
std2G5_stdx6	1	3.61533	1.82113	1.99	0.0506	1.79166

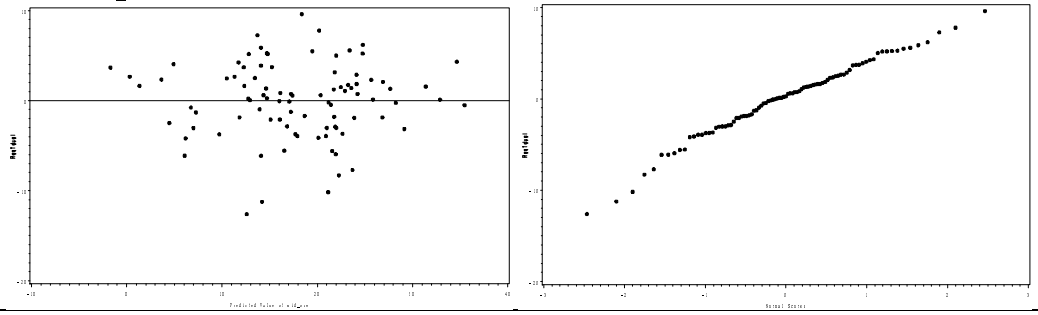


Figure A.9 Model A of MidOSW

Model B of MidOSW:

mid_osw = Selected state and decision variables and STD interaction terms (All Dec. and Selected Sta. V. from model B

Confirm for Model B

Dependent Variable: mid_osw

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	15	5249.84265	349.98951	19.83	<.0001
Error	75	1323.76174	17.65016		
Corrected Total	90	6573.60440			

Root MSE	4.20121	R-Square	0.7986
Dependent Mean	17.78022	Adj R-Sq	0.7583
Coeff Var	23.62855		

Parameter Estimates

Parameter Variable	DF	Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	31.98110	4.26394	7.50	<.0001	0
stp2G1_stdx7	1	-8.38580	1.84343	-4.55	<.0001	2.37116
std2G7_stdx33	1	-3.06076	0.67270	-4.55	<.0001	1.14426
stp2G9_stdx5	1	3.30472	0.97336	3.40	0.0011	1.13639
stp2G4_stdx37	1	3.43679	0.81691	4.21	<.0001	1.44091
std2G3_stdx24	1	-20.77166	6.85276	-3.03	0.0033	20.41162
std2G1_stdx37	1	-1.31717	0.57081	-2.31	0.0238	1.33158
std2G4_stdx6	1	3.24931	1.02396	3.17	0.0022	1.57953
stp2G1_stdx35	1	2.75842	1.02822	2.68	0.0090	1.12881
std2G2_stdx37	1	-3.20002	1.05391	-3.04	0.0033	2.76614
std2G8_stdx24	1	-6.59451	1.84174	-3.58	0.0006	1.15846
std2G6_stdx7	1	-3.65985	1.62041	-2.26	0.0268	2.35762
stp2G4_stdx6	1	-5.21833	1.13829	-4.58	<.0001	1.26834
D_2G3	1	-4.81124	1.98615	-2.42	0.0178	20.55205
std2G2_stdx24	1	4.14095	1.96173	2.11	0.0381	3.08144
std2G4_stdx7	1	-2.30924	1.21413	-1.90	0.0610	1.31538

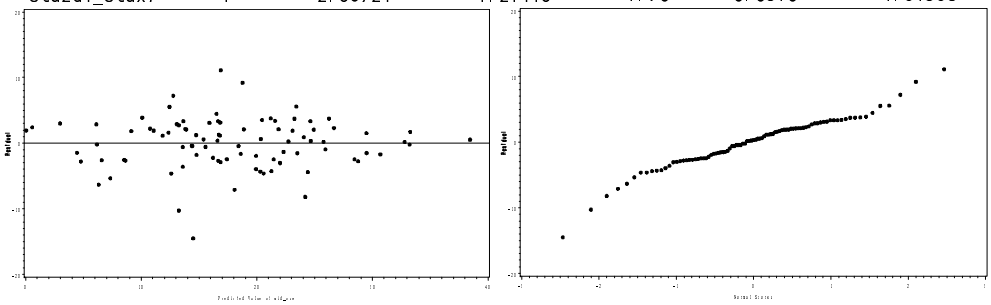


Figure A.10 Model B of MidOSW

Model C-1 of MidOSW:

mid_osw = ALL state and decision variables and STD interaction terms (from All Dec. and Sta.V.)

✓ **Model C Alpha=0.1**

Dependent Variable: mid_osw

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	23	5900.24098	256.53222	25.53	<.0001
Error	67	673.36342	10.05020		
Corrected Total	90	6573.60440			

Root MSE	3.17021	R-Square	0.8976
Dependent Mean	17.78022	Adj R-Sq	0.8624
Coeff Var	17.82995		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	25.02174	1.06663	23.46	<.0001	0
stp2G1_stdx7	1	-11.80073	1.09564	-10.77	<.0001	1.47101
std2G8_stdx6	1	-11.74243	1.24132	-9.46	<.0001	2.81252
sghxot2	1	-2.76481	0.37566	-7.36	<.0001	1.81117
std2G8_stdx28	1	-2.97343	1.09402	-2.72	0.0084	2.36553
stp2G9_stdx5	1	6.09761	1.06536	5.72	<.0001	2.39083
stp2G4_stdx47	1	2.77839	0.86219	3.22	0.0020	2.40917
std2G3_stdx46	1	-2.76287	0.58294	-4.74	<.0001	1.57987
stp2G9_stdx34	1	-4.07970	0.84583	-4.82	<.0001	4.74986
stp2G9_stdx43	1	7.31222	1.15903	6.31	<.0001	8.34297
std2G2_stdx37	1	-5.02116	0.89747	-5.59	<.0001	3.52279
std2G2_stdx5	1	-3.80406	1.25674	-3.03	0.0035	2.22322
std2G6_stdx28	1	-3.42026	1.06416	-3.21	0.0020	2.22961
stp2G9_stdx47	1	-3.95339	0.90717	-4.36	<.0001	5.62931
std2G7_stdx47	1	-4.81649	0.90459	-5.32	<.0001	2.60386
std2G3_stdx48	1	-1.73982	0.54081	-3.22	0.0020	1.58716
std2G2_stdx35	1	3.07160	0.95146	3.23	0.0019	3.69344
std2G3_stdx6	1	3.05284	1.34328	2.27	0.0263	2.66449
std2G2_stdx33	1	-2.72149	0.90145	-3.02	0.0036	3.65989
std2G2_stdx32	1	3.71721	0.94007	3.95	0.0002	3.92439
std2G1_stdx41	1	-1.23373	0.42600	-2.90	0.0051	1.35960
stp2G9_stdx40	1	1.05159	0.38613	2.72	0.0082	1.34856
stp2G4_stdx34	1	-1.38437	0.81125	-1.71	0.0926	2.31713
stp2G11_stdx52	1	1.00155	0.58866	1.70	0.0935	1.66936

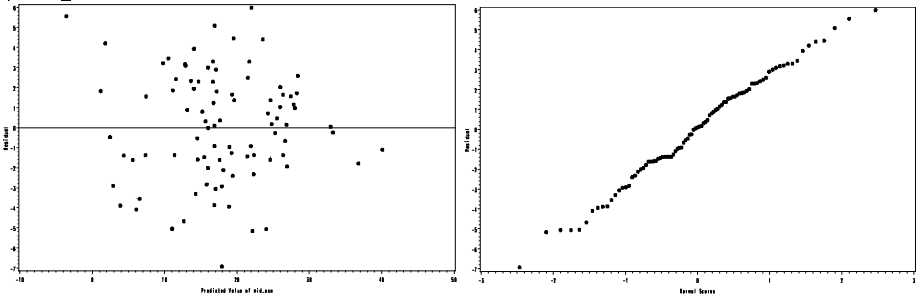


Figure A.11 Model C–1 of MidOSW

Model C-2 of MidOSW Alpha=0.05

Dependent Variable: mid_osw

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	9	5081.26636	564.58515	30.64	<.0001
Error	81	1492.33804	18.42393		
Corrected Total	90	6573.60440			

Root MSE	4.29231	R-Square	0.7730
Dependent Mean	17.78022	Adj R-Sq	0.7478
Coeff Var	24.14093		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	20.75118	0.95968	21.62	<.0001	0
stp2G1_stdx7	1	-11.93462	1.36548	-8.74	<.0001	1.24635
std2G8_stdx6	1	-8.18523	1.17388	-6.97	<.0001	1.37204
std2G7_stdx33	1	-2.27967	0.67286	-3.39	0.0011	1.09673
sghxot2	1	-1.27736	0.38418	-3.32	0.0013	1.03333
std2G8_stdx28	1	-3.78832	1.10915	-3.42	0.0010	1.32635
stp2G9_stdx5	1	2.68067	1.05541	2.54	0.0130	1.27994
stp2G4_stdx47	1	2.70258	0.77152	3.50	0.0008	1.05234
std2G3_stdx46	1	-2.67837	0.66538	-4.03	0.0001	1.12280
stp2G9_stdx34	1	-1.47310	0.61764	-2.39	0.0194	1.38157

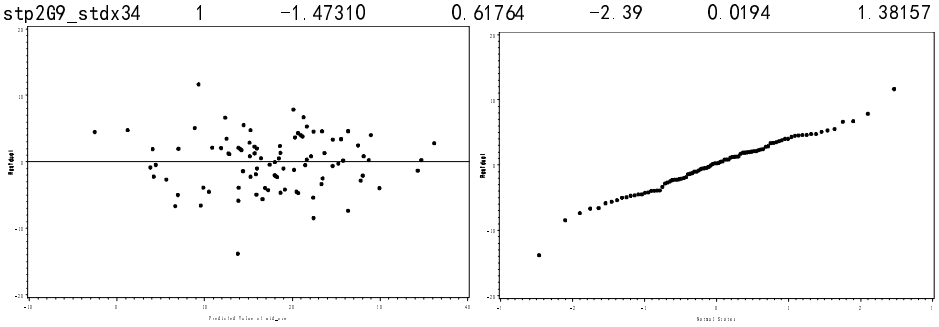


Figure A.12 Model C–2 of MidOSW

We want to choose the one with Alpha=0.01, but one of its variables has high VIF. So, we omit that variable and do try-and-error to get the cutoff alpha=0.055.

✓ Confirm Model C of MidOSW Alpha=0.055

Dependent Variable: mid_osw

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	5293.61013	441.13418	26.88	<.0001
Error	78	1279.99427	16.41018		
Corrected Total	90	6573.60440			

Root MSE	4.05095	R-Square	0.8053
Dependent Mean	17.78022	Adj R-Sq	0.7753
Coeff Var	22.78346		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	22.17623	1.00350	22.10	<.0001	0
stp2G1_stdx7	1	-12.24315	1.30578	-9.38	<.0001	1.27963
std2G8_stdx6	1	-8.66624	1.14024	-7.60	<.0001	1.45338
std2G7_stdx33	1	-2.47391	0.66854	-3.70	0.0004	1.21555
sghxot2	1	-2.01205	0.42194	-4.77	<.0001	1.39941
std2G8_stdx28	1	-4.24277	1.05811	-4.01	0.0001	1.35519
stp2G9_stdx5	1	3.67381	1.12320	3.27	0.0016	1.62754
stp2G4_stdx47	1	2.50107	0.73947	3.38	0.0011	1.08534
std2G3_stdx46	1	-2.98721	0.63987	-4.67	<.0001	1.16581
stp2G9_stdx34	1	-2.40793	0.80282	-3.00	0.0036	2.62069
stp2G9_stdx43	1	3.25301	1.04821	3.10	0.0027	4.17914
stp2G9_stdx32	1	-1.74235	0.73436	-2.37	0.0201	2.25923
sghxot1	1	-2.37303	1.13155	-2.10	0.0392	1.13350

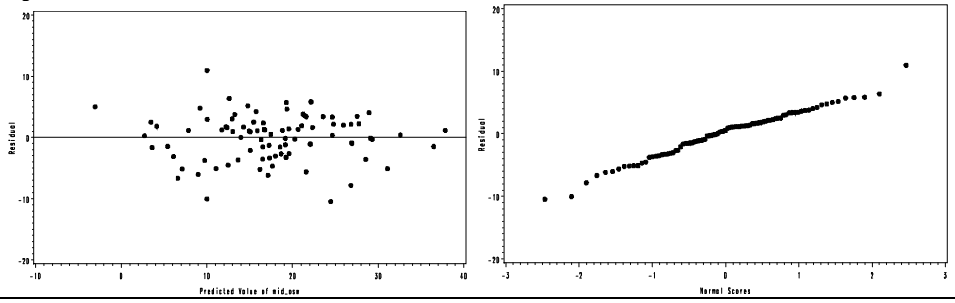


Figure A.13 Model C–3 of MidOSW

✓ Preliminary Model 1 of MidPDA

Confirm P-Model 1 Alpha=0.1

Dependent Variable: mid_pda

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	178.42142	25.48877	8.26	<.0001
Error	83	255.99616	3.08429		
Corrected Total	90	434.41758			

Root MSE	1.75621	R-Square	0.4107
Dependent Mean	5.13187	Adj R-Sq	0.3610
Coeff Var	34.22175		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-0.65778	1.34529	-0.49	0.6262	0
pre_osw	1	0.09024	0.02043	4.42	<.0001	1.08399
D_2G3	1	0.72055	0.18875	3.82	0.0003	1.06214
sghxot1	1	-1.14648	0.47036	-2.44	0.0169	1.04206
Pr_2G10	1	0.87446	0.42468	2.06	0.0426	1.06023
litigat	1	1.19234	0.54671	2.18	0.0320	1.07981
D_2G8	1	2.36032	0.95116	2.48	0.0151	1.12174
status	1	0.92792	0.40963	2.27	0.0261	1.11081

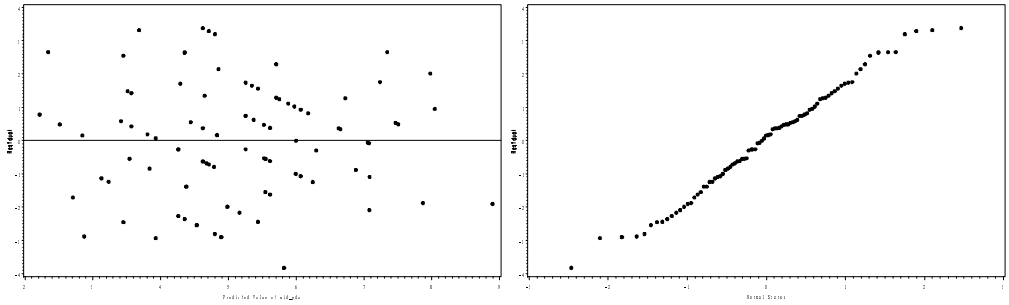


Figure A.14 Preliminary Model 1 of MidPDA

Preliminary Model 2 of MidPDA - SqrtY

Confirm P-Model 2 Alpha=0.1

Dependent Variable: SqrtY

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	8	11.55082	1.44385	7.34	<.0001
Error	82	16.13567	0.19678		
Corrected Total	90	27.68648			

Root MSE	0.44359	R-Square	0.4172
Dependent Mean	2.19718	Adj R-Sq	0.3603
Coeff Var	20.18924		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.89502	0.33299	2.69	0.0087	0
pre_osw	1	0.01813	0.00532	3.41	0.0010	1.15116
sghxot1	1	-0.32645	0.11910	-2.74	0.0075	1.04728
D_2G3	1	0.15792	0.04774	3.31	0.0014	1.06487
pastdxot	1	-0.47450	0.19042	-2.49	0.0147	1.03273
litigat	1	0.25926	0.13982	1.85	0.0673	1.10698
D_2G8	1	0.58279	0.23861	2.44	0.0167	1.10645
D_2G5	1	0.06794	0.03963	1.71	0.0902	1.16025
status	1	0.25937	0.10455	2.48	0.0152	1.13418

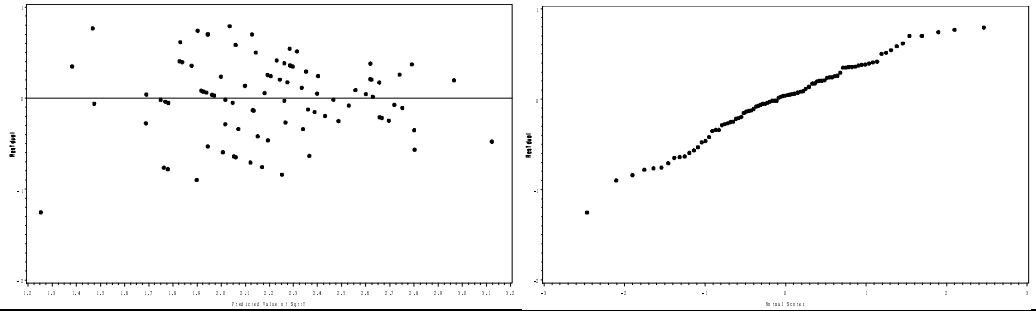


Figure A.15 Preliminary Model 2 of MidPDA

Model A of MidPDA:

mid_pda = ALL state and decision variables and STD interaction terms (All Dec.and Selected Sta.V.from mid_pda)

Confirm for Model A

Dependent Variable: mid_pda

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	8	244.87073	30.60884	13.24	<.0001
Error	82	189.54686	2.31155		
Corrected Total	90	434.41758			

Root MSE	1.52038	R-Square	0.5637
Dependent Mean	5.13187	Adj R-Sq	0.5211
Coeff Var	29.62620		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	6.72823	0.34771	19.35	<.0001	0
std2G6_dx7	1	-2.47746	0.39790	-6.23	<.0001	1.08549
std2G3_dx24	1	-5.02499	0.89396	-5.62	<.0001	2.65236
D_2G8	1	2.61334	0.86172	3.03	0.0032	1.22848
std2G3_dx35	1	1.25603	0.45512	2.76	0.0071	2.54988
std2G8_dx31	1	-0.48590	0.24252	-2.00	0.0484	1.27497
stp2G10_dx24	1	-0.97605	0.33259	-2.93	0.0043	1.10447
std2G4_dx31	1	-0.49264	0.17675	-2.79	0.0066	1.13312
D_2G6	1	-0.63111	0.26654	-2.37	0.0203	1.11120

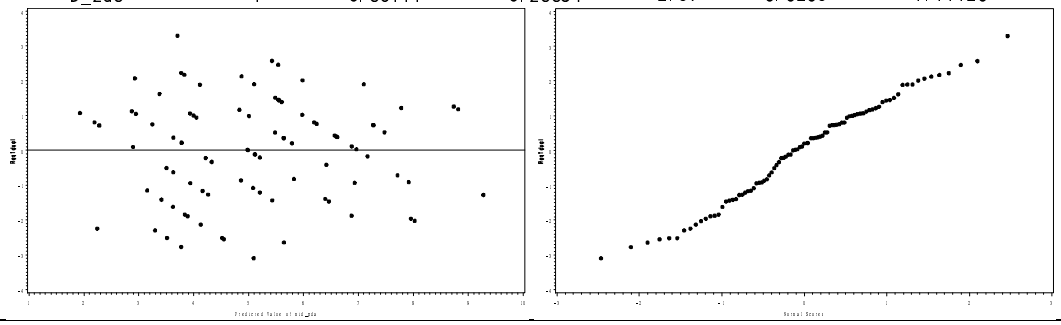


Figure A.16 Model A of MidPDA

Model B of MidPDA:

mid_pda = Selected state and decision variables and STD interaction terms (All Dec.and Selected Sta.V.from mid_pda)

Confirm for Model B

Dependent Variable: mid_pda

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	8	244.34677	30.54335	13.18	<.0001
Error	82	190.07081	2.31794		
Corrected Total	90	434.41758			

Root MSE	1.52248	R-Square	0.5625
Dependent Mean	5.13187	Adj R-Sq	0.5198
Coeff Var	29.66711		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	6.66095	0.34584	19.26	<.0001	0
std2G6_dx7	1	-2.52579	0.40191	-6.28	<.0001	1.10441
std2G3_dx24	1	-5.12603	0.89414	-5.73	<.0001	2.64609
D_2G8	1	2.14183	0.86155	2.49	0.0149	1.22462
std2G3_dx35	1	1.33913	0.45265	2.96	0.0040	2.51538
std2G8_dx31	1	-0.98386	0.29735	-3.31	0.0014	1.91148
stp2G10_dx24	1	-0.94711	0.33135	-2.86	0.0054	1.09325
std2G4_dx31	1	-0.47060	0.17542	-2.68	0.0088	1.11316
std2G6_dx31	1	0.56676	0.24470	2.32	0.0230	1.77530

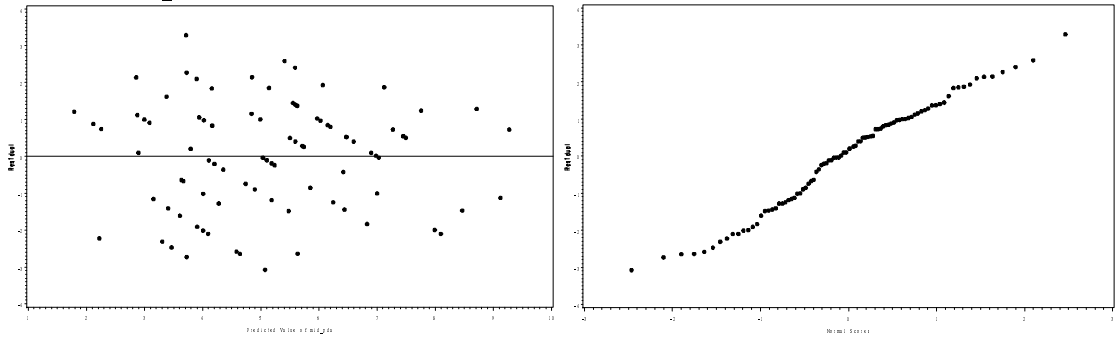


Figure A.17 Model B of MidPDA

Model C-1 of MidPDA:

mid_pda = ALL state and decision variables and STD interaction terms (from All Dec.and Sta.V.)

✓ Confirm Model C Alpha=0.018

Dependent Variable: mid_pda

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	370.91237	20.60624	23.36	<.0001
Error	72	63.50521	0.88202		
Corrected Total	90	434.41758			

Root MSE	0.93916	R-Square	0.8538
Dependent Mean	5.13187	Adj R-Sq	0.8173
Coeff Var	18.30050		

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	8.80639	0.37033	23.78	<.0001	0
std2G6_stdx7	1	-2.18497	0.26043	-8.39	<.0001	1.21862
stp2G9_stdx5	1	2.27773	0.37764	6.03	<.0001	3.42307
std2G8_stdx27	1	-2.19918	0.36056	-6.10	<.0001	1.75852
std2G5_stdx26	1	1.76109	0.33663	5.23	<.0001	1.26695
std2G3_stdx24	1	-9.12577	0.83595	-10.92	<.0001	6.07827
std2G3_stdx35	1	1.66096	0.30276	5.49	<.0001	2.95737
stp2G10_stdx50	1	-0.92915	0.12982	-7.16	<.0001	1.64619
std2G8_stdx31	1	-0.76828	0.15833	-4.85	<.0001	1.42417
stp2G11_stdx37	1	0.75482	0.16102	4.69	<.0001	1.47310
std2G4_stdx26	1	-1.82239	0.27093	-6.73	<.0001	1.71470
std2G7_stdx47	1	-0.87079	0.20629	-4.22	<.0001	1.54293
std2G3_stdx27	1	2.11988	0.48798	4.34	<.0001	4.21122
std2G1_stdx32	1	-0.90142	0.17387	-5.18	<.0001	2.41365
std2G2_stdx34	1	0.71954	0.15733	4.57	<.0001	1.31005
stp2G10_stdx5	1	-1.64229	0.37333	-4.40	<.0001	3.70338
std2G4_stdx43	1	-0.99258	0.14037	-7.07	<.0001	1.82310
stp2G10_stdx6	1	0.72732	0.22986	3.16	0.0023	1.57933
std2G1_stdx45	1	0.50584	0.17553	2.88	0.0052	2.26189

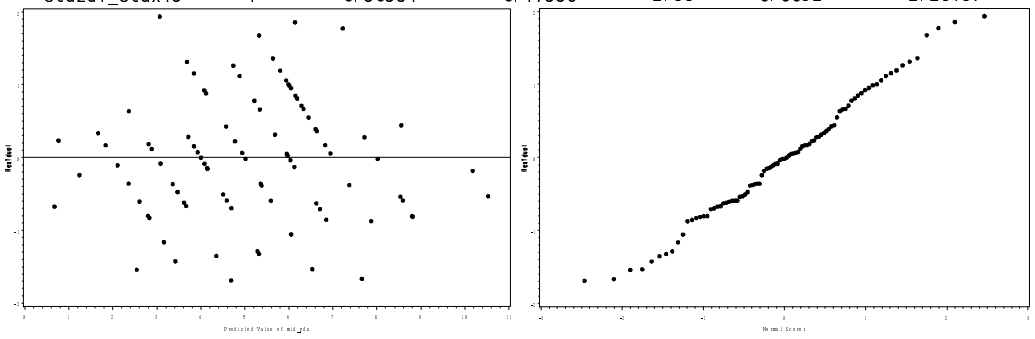


Figure A.18 Model C–1 of MidPDA

Confirm Model C-2 of MidPDA Alpha=0.01

Dependent Variable: mid_pda

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	4	196.36755	49.09189	17.74	<.0001
Error	86	238.05003	2.76802		
Corrected Total	90	434.41758			

Root MSE	1.66374	R-Square	0.4520
Dependent Mean	5.13187	Adj R-Sq	0.4265
Coeff Var	32.41973		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	6.58726	0.39225	16.79	<.0001	0
std2G6_stdx7	1	-2.30641	0.42570	-5.42	<.0001	1.03755
stp2G9_stdx5	1	1.28232	0.36594	3.50	0.0007	1.02419
std2G3_stdx34	1	-1.09166	0.30848	-3.54	0.0007	1.02264
std2G8_stdx27	1	-1.49221	0.48726	-3.06	0.0029	1.02335

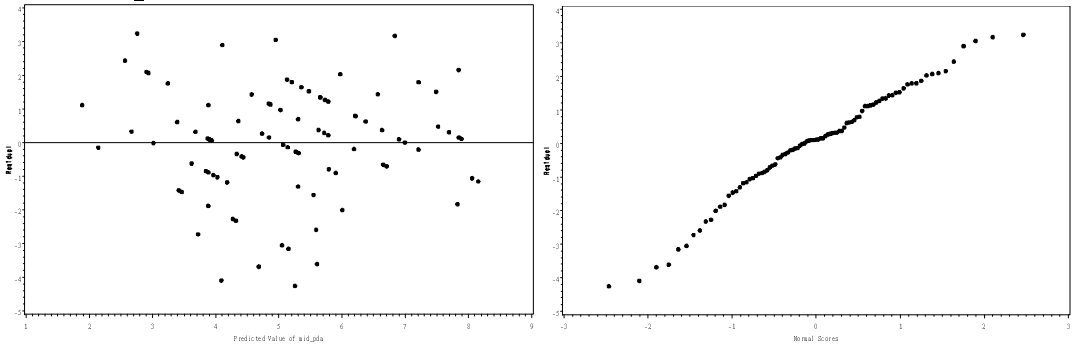


Figure A.19 Model C–2 of MidPDA

Mid_PDA - Model C-3: The cut off point of Alpha is 0.0164, which gives R-square =0.8236

Stepwise for Model C Alpha=0.0164

Dependent Variable: mid_pda

Summary of Stepwise Selection

Step	Variable Entered	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	std2G6_stdx7		1	0.2386	0.2386	.	27.89	<.0001
2	std2G3_stdx34		2	0.0892	0.3277	.	11.67	0.0010
3	stp2G9_stdx5		3	0.0645	0.3923	.	9.24	0.0031
4	std2G8_stdx27		4	0.0598	0.4520	.	9.38	0.0029
5	std2G5_stdx26		5	0.0394	0.4914	.	6.58	0.0121
6	std2G3_stdx24		6	0.0371	0.5285	.	6.60	0.0119
7		std2G3_stdx34	5	0.0137	0.5148	.	2.44	0.1221
8	std2G3_stdx35		6	0.0345	0.5493	.	6.44	0.0130
9	stp2G10_stdx50		7	0.0402	0.5895	.	8.13	0.0055
10	std2G8_stdx31		8	0.0280	0.6176	.	6.01	0.0163
11	std2G4_stdx39		9	0.0339	0.6514	.	7.87	0.0063
12	stp2G11_stdx37		10	0.0297	0.6811	.	7.45	0.0078
13	std2G4_stdx26		11	0.0240	0.7051	.	6.42	0.0132
14	std2G7_stdx47		12	0.0217	0.7268	.	6.20	0.0149
15	std2G3_stdx27		13	0.0241	0.7509	.	7.44	0.0079
16	std2G1_stdx32		14	0.0209	0.7718	.	6.96	0.0101
17	std2G2_stdx34		15	0.0181	0.7898	.	6.45	0.0132
18	stp2G10_stdx5		16	0.0193	0.8091	.	7.47	0.0079
19	std2G4_stdx43		17	0.0243	0.8334	.	10.67	0.0017
20		std2G4_stdx39	16	0.0098	0.8236	.	4.32	0.0413

Figure A.20 Model C–3 of MidPDA

Confirm Model C-4 of MidPDA_Alpha=0.0164

Dependent Variable: mid_pda

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	357.78355	22.36147	21.59	<.0001
Error	74	76.63404	1.03560		
Corrected Total	90	434.41758			

Root MSE	1.01764	R-Square	0.8236
Dependent Mean	5.13187	Adj R-Sq	0.7855
Coeff Var	19.82985		

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	8.72085	0.39328	22.17	<.0001	0
std2G6_stdx7	1	-2.30919	0.27986	-8.25	<.0001	1.19860
stp2G9_stdx5	1	2.15771	0.40372	5.34	<.0001	3.33193
std2G8_stdx27	1	-2.11061	0.38708	-5.45	<.0001	1.72619
std2G5_stdx26	1	2.02513	0.35570	5.69	<.0001	1.20484
std2G3_stdx24	1	-8.48676	0.87660	-9.68	<.0001	**5.6925**
std2G3_stdx35	1	1.48574	0.32086	4.63	<.0001	2.82886
stp2G10_stdx50	1	-0.68230	0.12072	-5.65	<.0001	1.21230
std2G8_stdx31	1	-0.79462	0.16985	-4.68	<.0001	1.39590
stp2G11_stdx37	1	0.74111	0.17312	4.28	<.0001	1.45025
std2G4_stdx26	1	-1.79681	0.29347	-6.12	<.0001	1.71359
std2G7_stdx47	1	-0.80283	0.22263	-3.61	0.0006	1.53063
std2G3_stdx27	1	1.93429	0.52617	3.68	0.0004	4.17010
std2G1_stdx32	1	-0.54530	0.13727	-3.97	0.0002	1.28137
std2G2_stdx34	1	0.65551	0.16913	3.88	0.0002	1.28937
stp2G10_stdx5	1	-1.43303	0.39274	-3.65	0.0005	3.49081
std2G4_stdx43	1	-0.88742	0.14878	-5.96	<.0001	1.74423

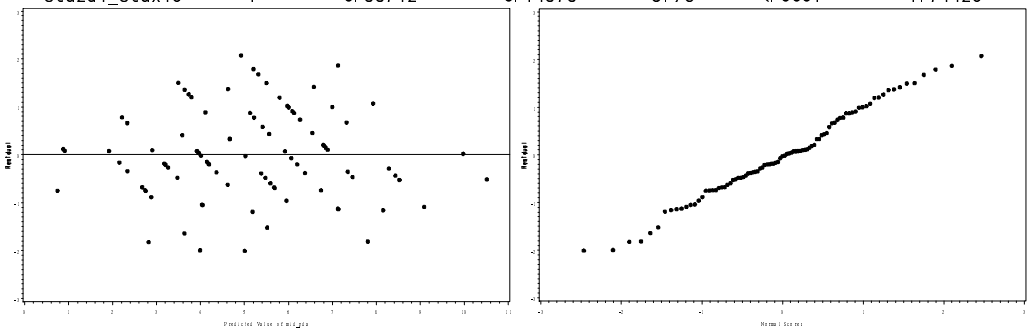


Figure A.21 Model C–4 of MidPDA

Mid_PDA-Model C-5 after taking off “ std2G3_stdx24 “ (VIF=5.69) with Alpha = 0.05,

Summary of Stepwise Selection

Step	Variable Entered	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	std2G6_stdx7		1	0.2386	0.2386	.	27.89	<.0001
2	std2G3_stdx34		2	0.0892	0.3277	.	11.67	0.0010
3	stp2G9_stdx5		3	0.0645	0.3923	.	9.24	0.0031
4	std2G8_stdx27		4	0.0598	0.4520	.	9.38	0.0029
5	std2G5_stdx26		5	0.0394	0.4914	.	6.58	0.0121
6	std2G6_stdx36		6	0.0343	0.5257	.	6.07	0.0158
7	std2G3_stdx48		7	0.0389	0.5646	.	7.42	0.0079
8	stp2G10_stdx51		8	0.0379	0.6026	.	7.83	0.0064
9	std2G4_stdx44		9	0.0298	0.6324	.	6.57	0.0122
10	std2G1_stdx32		10	0.0248	0.6572	.	5.80	0.0184
11	age		11	0.0242	0.6814	.	6.01	0.0164
12	std2G3_stdx30		12	0.0245	0.7059	.	6.49	0.0128
13	std2G2_stdx53		13	0.0216	0.7275	.	6.10	0.0157
14	stp2G11_stdx28		14	0.0190	0.7465	.	5.69	0.0195
15	std2G6_stdx6		15	0.0155	0.7620	.	4.89	0.0300
16	stp2G1_stdx50		16	0.0208	0.7828	.	7.08	0.0096
17	std2G4_stdx29		17	0.0233	0.8061	.	8.76	0.0041
18	std2G4_stdx40		18	0.0182	0.8242	.	7.44	0.0080
19	std2G8_stdx52		19	0.0177	0.8420	.	7.97	0.0062
20	stp2G10_stdx37		20	0.0105	0.8525	.	4.98	0.0288
21	std2G5_stdx6		21	0.0097	0.8622	.	4.85	0.0309
22	std2G6_stdx50		22	0.0101	0.8723	.	5.38	0.0234
23	stp2G9_stdx30		23	0.0082	0.8805	.	4.60	0.0355
24	stp2G9_stdx34		24	0.0069	0.8874	.	4.06	0.0481
25	std2G4_stdx47		25	0.0076	0.8950	.	4.68	0.0342
26	stp2G1_stdx29		26	0.0066	0.9016	.	4.31	0.0418

Figure A.22 Model C–5 of MidPDA

Confirm Model C-6 of MidPDA Alpha=0.05

Dependent Variable: mid_pda

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	26	391.66920	15.06420	22.55	<.0001
Error	64	42.74838	0.66794		
Corrected Total	90	434.41758			

Root MSE	0.81728	R-Square	0.9016
Dependent Mean	5.13187	Adj R-Sq	0.8616
Coeff Var	15.92555		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	11.03099	0.93434	11.81	<.0001	0
std2G6_stdx7	1	-2.70524	0.25685	-10.53	<.0001	1.56524
std2G3_stdx34	1	-0.90614	0.20363	-4.45	<.0001	1.84672
stp2G9_stdx5	1	0.57669	0.23039	2.50	0.0149	1.68229
std2G8_stdx27	1	-1.39740	0.30108	-4.64	<.0001	1.61919
std2G5_stdx26	1	1.80848	0.29572	6.12	<.0001	1.29111
std2G6_stdx36	1	1.28708	0.16287	7.90	<.0001	1.54466
std2G3_stdx48	1	-0.59807	0.15908	-3.76	0.0004	2.06636
stp2G10_stdx51	1	-0.43740	0.12902	-3.39	0.0012	1.96975
std2G4_stdx44	1	-0.72365	0.15466	-4.68	<.0001	2.31641
std2G1_stdx32	1	-0.71621	0.11874	-6.03	<.0001	1.48628
age	1	-0.08057	0.01623	-4.96	<.0001	8.81553
std2G3_stdx30	1	-1.28929	0.24036	-5.36	<.0001	1.92351
std2G2_stdx53	1	0.83839	0.14379	5.83	<.0001	1.37123
stp2G11_stdx28	1	-1.65073	0.51128	-3.23	0.0020	7.78061
std2G6_stdx6	1	-1.54179	0.27448	-5.62	<.0001	2.32489
stp2G1_stdx50	1	0.34616	0.15861	2.18	0.0328	2.05116
std2G4_stdx29	1	-0.98691	0.21730	-4.54	<.0001	2.22377
std2G4_stdx40	1	-0.25207	0.09991	-2.52	0.0141	1.27941
std2G8_stdx52	1	-0.79142	0.17327	-4.57	<.0001	1.74160
stp2G10_stdx37	1	-0.44570	0.12838	-3.47	0.0009	2.07603
std2G5_stdx6	1	0.79048	0.34472	2.29	0.0251	1.89407
std2G6_stdx50	1	0.49643	0.15436	3.22	0.0020	2.45152
stp2G9_stdx30	1	0.74802	0.23097	3.24	0.0019	2.74265
stp2G9_stdx34	1	-0.37484	0.14476	-2.59	0.0119	2.09333
std2G4_stdx47	1	0.37959	0.14870	2.55	0.0131	2.75386
stp2G1_stdx29	1	0.48874	0.23533	2.08	0.0418	1.47813

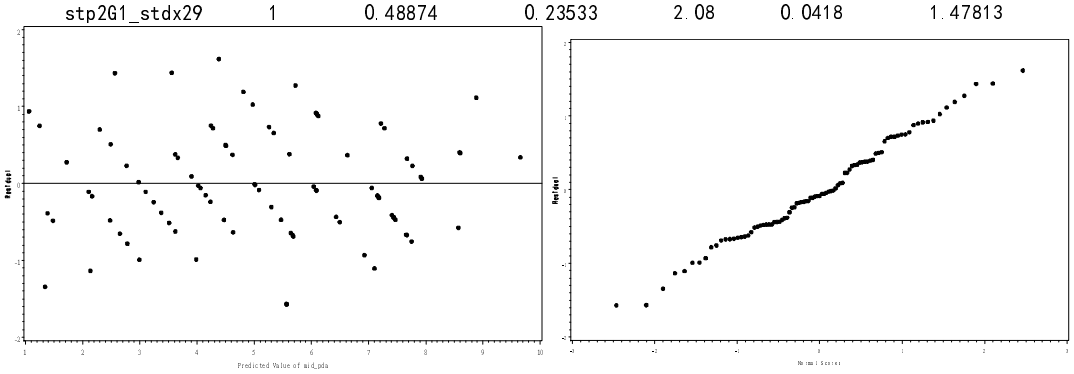


Figure A.23 Model C–6 of MidPDA

Confirm Model C -7 of MidPDA_Alpha=0.031
(after taking off " std2G3_stdx24 " the cut-off point of Alpha becomes 0.031)

Dependent Variable: mid_pda

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	19	369.12755	19.42777	21.13	<.0001
Error	71	65.29003	0.91958		
Corrected Total	90	434.41758			

Root MSE	0.95895	R-Square	0.8497
Dependent Mean	5.13187	Adj R-Sq	0.8095
Coeff Var	18.68610		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	9.05396	0.64273	14.09	<.0001	0
std2G6_stdx7	1	-2.25761	0.27685	-8.15	<.0001	1.32090
std2G3_stdx34	1	-0.73797	0.22710	-3.25	0.0018	1.66834
stp2G9_stdx5	1	0.67196	0.23237	2.89	0.0051	1.24308
std2G5_stdx26	1	1.85142	0.33847	5.47	<.0001	1.22853
std2G6_stdx36	1	0.99424	0.17669	5.63	<.0001	1.32056
std2G3_stdx48	1	-0.53090	0.15743	-3.37	0.0012	1.46984
stp2G10_stdx51	1	-0.49264	0.13922	-3.54	0.0007	1.66588
std2G1_stdx32	1	-0.76914	0.13475	-5.71	<.0001	1.39037
age	1	-0.02901	0.00754	-3.85	0.0003	1.38230
std2G3_stdx30	1	-1.20886	0.27516	-4.39	<.0001	1.83111
std2G2_stdx53	1	0.84259	0.16381	5.14	<.0001	1.29266
std2G6_stdx6	1	-1.34036	0.30334	-4.42	<.0001	2.06247
stp2G1_stdx50	1	0.70099	0.15950	4.40	<.0001	1.50646
std2G4_stdx29	1	-0.89964	0.21188	-4.25	<.0001	1.53563
std2G4_stdx40	1	-0.37166	0.11138	-3.34	0.0014	1.15491
std2G8_stdx52	1	-2.03052	0.36640	-5.54	<.0001	5.65679
pastdx11	1	-1.46281	0.41498	-3.52	0.0007	6.25201
stp2G10_stdx37	1	-0.37675	0.13461	-2.80	0.0066	1.65788
std2G4_stdx30	1	-0.48498	0.19436	-2.50	0.0149	1.55661

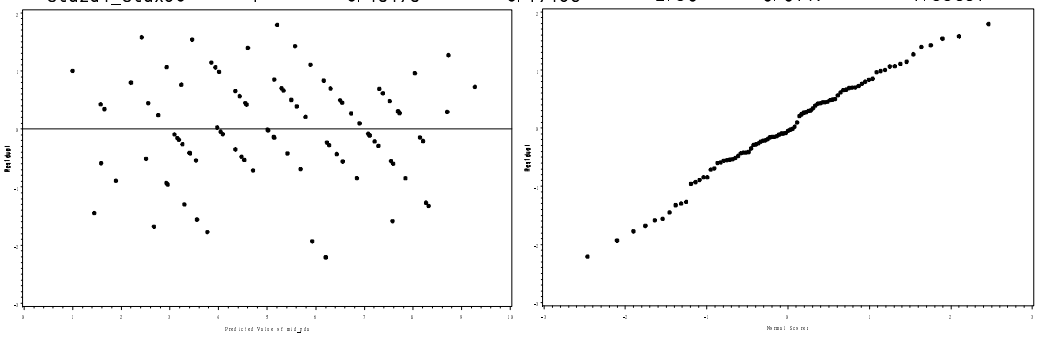


Figure A.24 Model C–7 of MidPDA

Preliminary Model 1of PostBDI

Confirm P-Model 1 Alpha=0.1

Dependent Variable: post_bdi

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	4973.48696	828.91449	40.62	<.0001
Error	82	1673.38945	20.40719		
Corrected Total	88	6646.87640			

Root MSE	4.51743	R-Square	0.7482
Dependent Mean	8.88764	Adj R-Sq	0.7298
Coeff Var	50.82824		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-4.71075	2.12541	-2.22	0.0294	0
mid_bdi	1	0.71339	0.05408	13.19	<.0001	1.19221
D_3G4	1	1.78807	0.53891	3.32	0.0014	1.08447
D_3G7	1	-3.08240	0.92755	-3.32	0.0013	1.13593
D_3G6	1	1.50685	0.70602	2.13	0.0358	1.14336
paintype	1	1.32893	0.59310	2.24	0.0278	1.14076
Pr_3G11	1	2.89386	1.53186	1.89	0.0624	1.02069

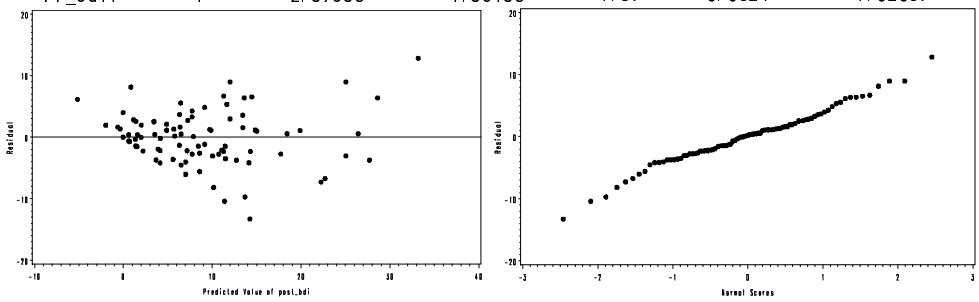


Figure A.25 Preliminary Model 1 of PostBDI

✓ Preliminary Model 2 of PostBDI - SqrtY

Confirm P-Model 2 Alpha=0.1

Dependent Variable: SqrtY

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	166.55624	11.89687	24.11	<.0001
Error	74	36.52009	0.49351		
Corrected Total	88	203.07634			

Root MSE	0.70251	R-Square	0.8202
Dependent Mean	2.57019	Adj R-Sq	0.7861
Coeff Var	27.33283		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.79614	0.45328	1.76	0.0832	0
mid_bdi	1	0.09830	0.01337	7.35	<.0001	3.01470
paintype	1	0.38721	0.09982	3.88	0.0002	1.33606
D_3G7	1	-0.68834	0.16155	-4.26	<.0001	1.42483
phydx3	1	-1.09150	0.25330	-4.31	<.0001	1.15400
pastdx6	1	-1.06307	0.22721	-4.68	<.0001	1.73241
S_G2	1	0.81650	0.25947	3.15	0.0024	1.21091
D_2G4	1	0.43712	0.08921	4.90	<.0001	1.30827
pre_bdi	1	0.04284	0.01431	2.99	0.0038	3.62711
phyd11	1	0.37092	0.14648	2.53	0.0135	1.57402
marital	1	-0.22462	0.08345	-2.69	0.0088	1.10847
phydx4	1	0.46540	0.18268	2.55	0.0129	1.21571
pre_pda	1	-0.15410	0.04676	-3.30	0.0015	1.20277
Pr_2G9	1	0.46576	0.20180	2.31	0.0238	1.13480
D_2G2	1	-0.16671	0.08296	-2.01	0.0481	1.35097

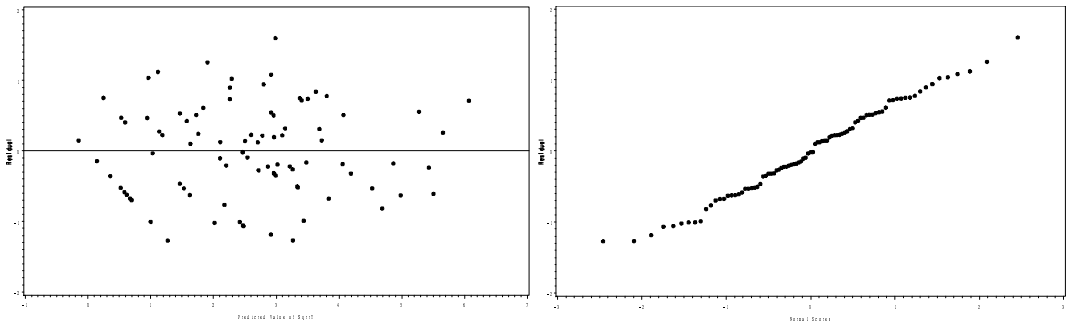


Figure A.26 Preliminary Model 2 of PostBDI

Model A of PostBDI:

SqrtY = all state and decision variables and STD interaction terms

Model A-1 with Alpha = 0.1 has R-Square =1 and over 100 variables

Confirm for Model A with Alpha = 0.05

Dependent Variable: SqrtY

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	31	198.57392	6.40561	81.09	<.0001
Error	57	4.50241	0.07899		
Corrected Total	88	203.07634			

Root MSE	0.28105	R-Square	0.9778
Dependent Mean	2.57019	Adj R-Sq	0.9658

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.46138	0.32359	4.52	<.0001	0
mid_bdi	1	0.09565	0.00471	20.30	<.0001	2.33891
std3G7_stdx26	1	-0.83917	0.09384	-8.94	<.0001	2.01816
D_3G4	1	0.41508	0.04416	9.40	<.0001	1.88171
stp2G1_stdx37	1	0.60463	0.09722	6.22	<.0001	4.45501
stp3G4_stdx33	1	-0.38491	0.05706	-6.75	<.0001	1.54798
stp3G1_stdx44	1	-0.48286	0.05262	-9.18	<.0001	1.96400
std2G5_stdx6	1	-1.33713	0.14085	-9.49	<.0001	2.61200
pre_osw	1	-0.02391	0.00480	-4.98	<.0001	2.30217
std2G7_stdx50	1	0.43849	0.07118	6.16	<.0001	3.69243
std3G2_stdx29	1	0.84107	0.09379	8.97	<.0001	1.99191
age	1	0.02330	0.00264	8.82	<.0001	1.90938
D_2G7	1	0.55200	0.06505	8.49	<.0001	1.82380
std2G1_stdx5	1	0.28952	0.07373	3.93	0.0002	1.54000
std3G7_stdx37	1	0.56032	0.07964	7.04	<.0001	3.95314
status	1	-0.25808	0.08070	-3.20	0.0023	1.68027
std2G4_stdx5	1	0.59375	0.08213	7.23	<.0001	2.11101
stp3G11_stdx37	1	-0.32385	0.05912	-5.48	<.0001	2.32270
pastdx7	1	0.59302	0.10797	5.49	<.0001	2.11924
std2G7_stdx6	1	-0.44425	0.15119	-2.94	0.0048	3.32232
stp2G4_stdx29	1	-0.57113	0.08513	-6.71	<.0001	1.90898
stp2G10_stdx29	1	-0.62225	0.08456	-7.36	<.0001	2.64232
num_pt2	1	-0.03321	0.00882	-3.77	0.0004	1.68561
phydxoth	1	0.37458	0.09925	3.77	0.0004	1.38446
std2G3_stdx5	1	0.52663	0.10774	4.89	<.0001	2.11652
std3G2_stdx38	1	-0.19138	0.04483	-4.27	<.0001	1.45378
stp2G10_stdx37	1	0.29157	0.05426	5.37	<.0001	3.05590
stp2G9_stdx44	1	-0.19848	0.05492	-3.61	0.0006	2.26944
stp2G4_stdx50	1	0.23930	0.06972	3.43	0.0011	3.69344
std2G6_stdx50	1	-0.20358	0.05530	-3.68	0.0005	2.63976

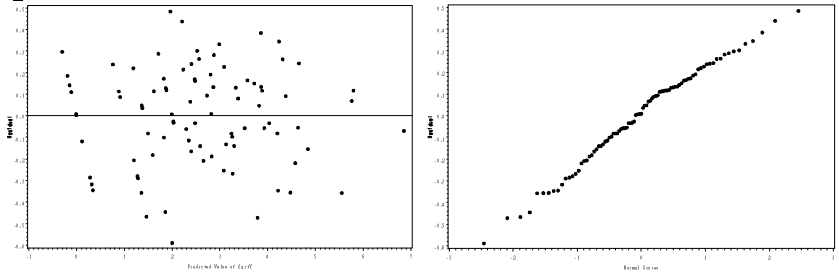


Figure A.27 Model A–1 of PostBDI

Model A-2 with Alpha = 0.01

Dependent Variable: SqrtY

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	154.33480	25.72247	43.27	<.0001
Error	82	48.74154	0.59441		
Corrected Total	88	203.07634			

Root MSE	0.77098	R-Square	0.7600
Dependent Mean	2.57019	Adj R-Sq	0.7424
Coeff Var	29.99696		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.81640	0.18115	4.51	<.0001	0
mid_bdi	1	0.11664	0.00875	13.33	<.0001	1.07191
std3G7_stdx26	1	-0.77679	0.18631	-4.17	<.0001	1.05708
D_3G4	1	0.38216	0.09236	4.14	<.0001	1.09358
stp2G1_stdx37	1	0.46861	0.12791	3.66	0.0004	1.02491
stp2G9_stdx50	1	-0.28515	0.08872	-3.21	0.0019	1.07018
stp3G4_stdx33	1	-0.36039	0.13322	-2.71	0.0083	1.12118

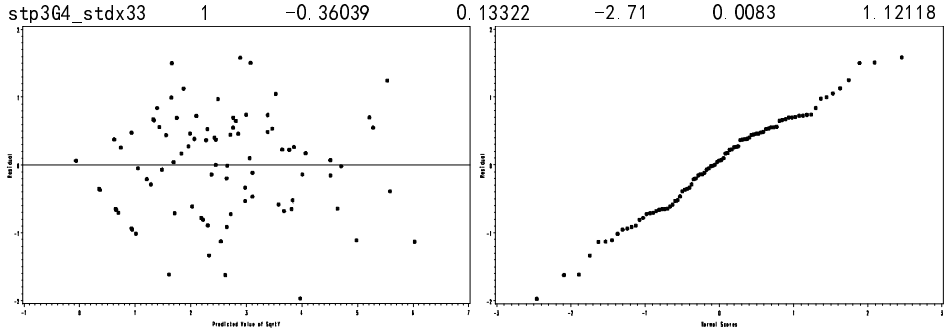


Figure A.28 Model A–2 of PostBDI

Model B of PostBDI:

SqrtY = selected state and decision variables and STD interaction terms (All Dec. and Selected Sta. V. from SqrtY)

Confirm for Model B

Dependent Variable: SqrtY

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	28	195.31818	6.97565	53.95	<.0001
Error	60	7.75816	0.12930		
Corrected Total	88	203.07634			

Root MSE	0.35959	R-Square	0.9618
Dependent Mean	2.57019	Adj R-Sq	0.9440
Coeff Var	13.99066		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.75593	0.16599	10.58	<.0001	0
mid_bdi	1	0.10804	0.00656	16.46	<.0001	2.77062
std3G7_stdx26	1	-1.97282	0.20970	-9.41	<.0001	6.15611
D_2G4	1	0.39055	0.07809	5.00	<.0001	3.82566
stp2G1_stdx37	1	0.50753	0.09989	5.08	<.0001	2.87311
stp3G11_stdx5	1	0.89803	0.10710	8.38	<.0001	1.73876
std2G5_stdx6	1	-1.36463	0.17175	-7.95	<.0001	2.37257
std2G7_stdx26	1	1.47693	0.22724	6.50	<.0001	6.42190
stp2G11_stdx50	1	0.46782	0.08961	5.22	<.0001	4.85610
std2G5_stdx37	1	0.39546	0.10389	3.81	0.0003	2.48446
stp2G10_stdx29	1	-0.50950	0.09844	-5.18	<.0001	2.18764
stp3G11_stdx37	1	-0.51838	0.08022	-6.46	<.0001	2.61230
std2G8_stdx50	1	-0.42410	0.09078	-4.67	<.0001	4.46809
std3G4_stdx50	1	0.74269	0.13135	5.65	<.0001	6.06501
std3G4_stdx6	1	-1.00656	0.22153	-4.54	<.0001	4.86396
std3G3_stdx29	1	-1.00479	0.14560	-6.90	<.0001	3.34994
std3G2_stdx29	1	0.48812	0.11752	4.15	0.0001	1.91058
std2G7_stdx50	1	-0.42000	0.11153	-3.77	0.0004	5.53660
std2G2_stdx50	1	0.19322	0.07112	2.72	0.0086	1.73489
stp3G1_stdx44	1	-0.39756	0.06585	-6.04	<.0001	1.87871
stp3G1_stdx29	1	0.44396	0.10404	4.27	<.0001	2.34204
stp2G10_stdx33	1	0.11842	0.05835	2.03	0.0469	2.09476
stp2G9_stdx50	1	-0.12738	0.05676	-2.24	0.0285	2.01313
std3G2_stdx38	1	-0.28856	0.06873	-4.20	<.0001	2.08723
stp3G11_stdx29	1	0.35103	0.13704	2.56	0.0130	3.85797
std2G4_stdx44	1	-0.15022	0.07390	-2.03	0.0465	2.70500
std2G4_stdx29	1	-0.30771	0.11239	-2.74	0.0081	2.97463
std3G5_stdx26	1	-0.30555	0.13042	-2.34	0.0225	1.85294
std3G6_stdx6	1	0.34630	0.18567	1.87	0.0671	4.31442

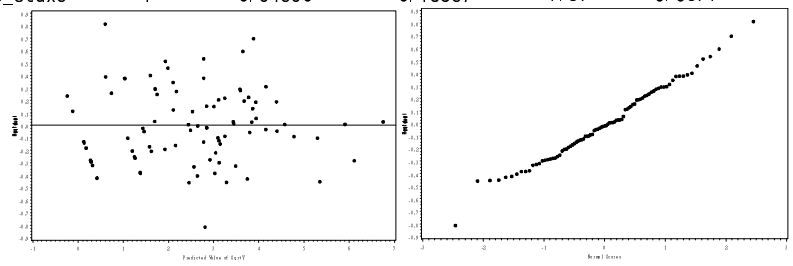


Figure A.29 Model B of PostBDI

Model C of PostBDI:

SqrtY = ALL state and decision variables and STD interaction terms (from All Dec.and Sta.V.)

Model C with Alpha = 0.1 and 0.05 have R-Square =1 and over 100 variables

✓ Confirm Model C Alpha=0.01

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	175.84954	15.98632	45.21	<.0001
Error	77	27.22679	0.35359		
Corrected Total	88	203.07634			

Root MSE	0.59464	R-Square	0.8659
Dependent Mean	2.57019	Adj R-Sq	0.8468
Coeff Var	23.13595		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.45830	0.18572	7.85	<.0001	0
mid_bdi	1	0.07807	0.00971	8.04	<.0001	2.21960
std3G7_stdx26	1	-1.05180	0.14833	-7.09	<.0001	1.12625
std2G4_stdx42	1	-0.24232	0.06850	-3.54	0.0007	1.09323
stp2G1_stdx37	1	0.81319	0.10865	7.48	<.0001	1.24312
stp3G9_stdx51	1	0.30345	0.06669	4.55	<.0001	1.11930
stp3G11_stdx39	1	-0.26796	0.08632	-3.10	0.0027	1.21037
std3G2_stdx23	1	0.47443	0.11503	4.12	<.0001	1.08947
std3G7_stdx51	1	-0.38071	0.09042	-4.21	<.0001	1.29738
stp2G9_stdx22	1	-0.48024	0.11636	-4.13	<.0001	1.19234
std3G5_stdx40	1	0.27401	0.08410	3.26	0.0017	1.18016
stp3G4_stdx6	1	-0.67401	0.22013	-3.06	0.0030	2.26462

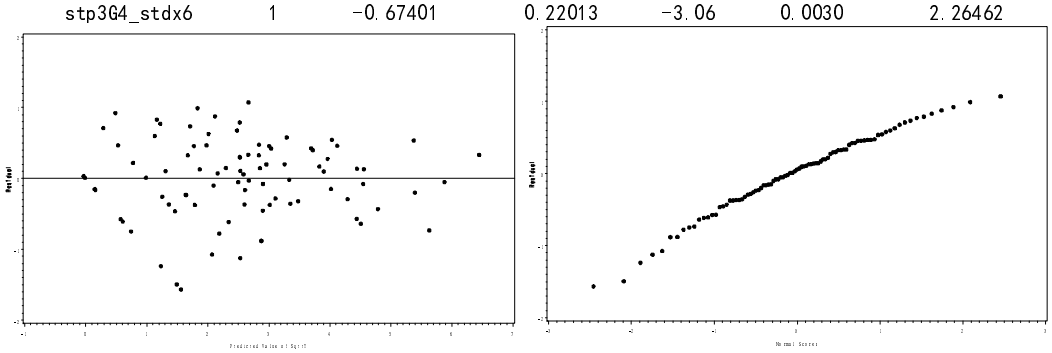


Figure A.30 Model C of PostBDI

Preliminary Model 1 of PostOSW

Confirm P-Model 1 Alpha=0.1

Dependent Variable: post_osw

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	4342.07312	723.67885	37.05	<.0001
Error	82	1601.81453	19.53432		
Corrected Total	88	5943.88764			

Root MSE	4.41977	R-Square	0.7305
Dependent Mean	16.33708	Adj R-Sq	0.7108
Coeff Var	27.05358		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	4.21184	2.46245	1.71	0.0910	0
mid_osw	1	0.80923	0.05922	13.66	<.0001	1.17454
D_3G3	1	1.96822	0.63826	3.08	0.0028	1.09473
D_3G2	1	1.12750	0.46121	2.44	0.0166	1.05738
Pr_2G4	1	2.61420	1.25615	2.08	0.0405	1.05825
phyd9	1	7.33803	2.87519	2.55	0.0126	1.22677
txassign	1	-1.02793	0.49932	-2.06	0.0427	1.15184

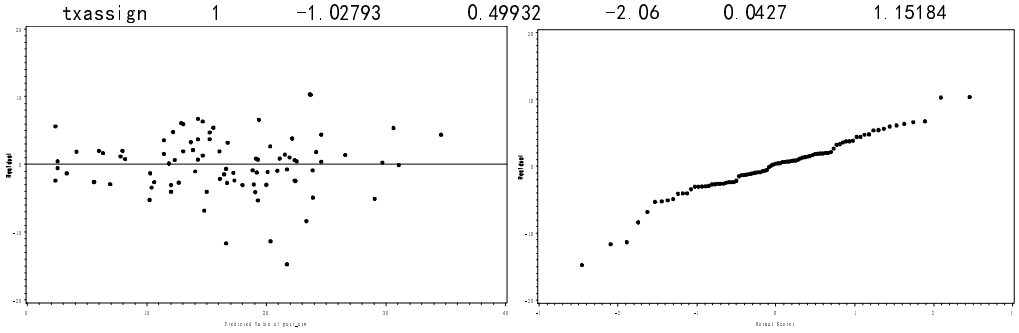


Figure A.31 Preliminary Model 1 of PostOSW

✓ Preliminary Model 2 od PostOSW - SqrtY

Confirm P-Model 2 Alpha=0.1

Dependent Variable: SqrtY

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	81.96620	16.39324	43.08	<.0001
Error	83	31.58160	0.38050		
Corrected Total	88	113.54780			

Root MSE	0.61685	R-Square	0.7219
Dependent Mean	3.88088	Adj R-Sq	0.7051
Coeff Var	15.89452		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.59203	0.18075	8.81	<.0001	0
mid_osw	1	0.08848	0.01100	8.04	<.0001	2.08190
phyd9	1	0.90431	0.37917	2.38	0.0194	1.09533
D_3G3	1	0.23732	0.08861	2.68	0.0089	1.08313
pre_osw	1	0.02479	0.00952	2.60	0.0109	1.87966
S_G1	1	0.48921	0.22990	2.13	0.0363	1.01137

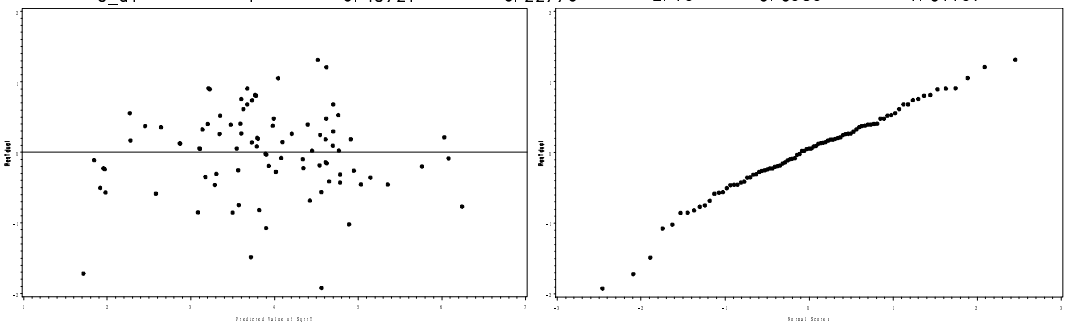


Figure A.32 Preliminary Model 2 of PostOSW

Model A of PostOSW:

SqrtY = all state and decision variables and STD interaction terms (All Dec.and Selected Sta.V.from SqrtY)

Confirm for Model A

Dependent Variable: SqrtY

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	20	99.92262	4.99613	24.93	<.0001
Error	68	13.62519	0.20037		
Corrected Total	88	113.54780			

Root MSE	0.44763	R-Square	0.8800
Dependent Mean	3.88088	Adj R-Sq	0.8447
Coeff Var	11.53416		

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	3.70467	0.34719	10.67	<.0001	0
mid_osw	1	0.08079	0.00987	8.18	<.0001	3.18277
stp3G9_stdx2	1	-0.29854	0.15592	-1.91	0.0597	2.10037
std3G3_stdx32	1	-0.36587	0.08781	-4.17	<.0001	1.60128
stp3G9_stdx43	1	0.46412	0.08268	5.61	<.0001	3.01732
Pr_3G10	1	0.57630	0.16081	3.58	0.0006	2.81019
txassign	1	-0.17583	0.05956	-2.95	0.0043	1.59762
pastdx	1	0.37538	0.17444	2.15	0.0350	2.08864
std2G5_stdx7	1	-0.90257	0.23088	-3.91	0.0002	2.08314
std3G6_stdx32	1	0.28432	0.09705	2.93	0.0046	1.71764
marital	1	-0.16087	0.05700	-2.82	0.0063	1.27405
phydx7	1	0.43516	0.12540	3.47	0.0009	1.17286
pastdx3	1	-0.61873	0.21082	-2.93	0.0045	1.61507
stp2G4_stdx43	1	-0.56445	0.13891	-4.06	0.0001	1.90234
phydx4	1	0.35215	0.15214	2.31	0.0237	2.07666
stp3G1_stdx2	1	-0.61672	0.17633	-3.50	0.0008	2.28141
D_2G7	1	0.27417	0.10108	2.71	0.0085	1.73617
phydxoth	1	0.33070	0.14970	2.21	0.0305	1.24153
pre_bdi	1	-0.01997	0.00754	-2.65	0.0101	2.48047
duration	1	0.00211	0.00103	2.04	0.0455	1.45207
stp2G11_stdx7	1	-0.31491	0.16445	-1.91	0.0597	2.11909

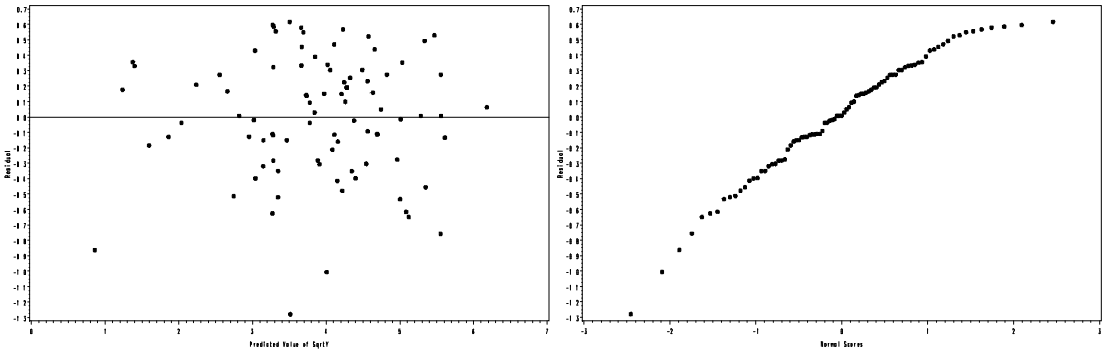


Figure A.33 Model A of PostOSW

Model B of PostOSW:

SqrtY = selected state and decision variables and STD interaction terms (All Dec.and Selected Sta.V.from SqrtY)

Confirm for Model B

Dependent Variable: SqrtY

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	86.07648	14.34608	42.82	<.0001
Error	82	27.47132	0.33502		
Corrected Total	88	113.54780			

Root MSE	0.57881	R-Square	0.7581
Dependent Mean	3.88088	Adj R-Sq	0.7404
Coeff Var	14.91428		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	2.41603	0.20185	11.97	<.0001	0
mid_osw	1	0.09409	0.00947	9.94	<.0001	1.74987
stp3G9_stdx2	1	-0.64953	0.16975	-3.83	0.0003	1.48900
std3G3_stdx32	1	-0.27976	0.09104	-3.07	0.0029	1.02947
std3G1_stdx7	1	-0.74347	0.24950	-2.98	0.0038	2.66454
stp3G9_stdx43	1	0.16872	0.07383	2.29	0.0249	1.43913
stp3G1_stdx7	1	0.35840	0.20858	1.72	0.0895	2.05765

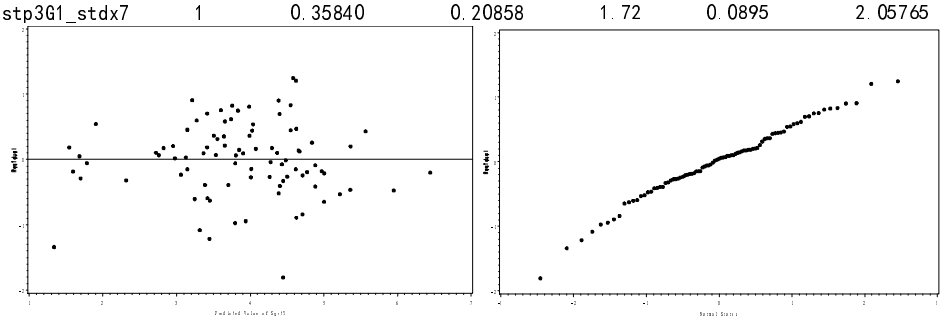


Figure A.34 Model B of PostOSW

Model C-1 of PostOSW:

SqrtY = ALL state and decision variables and STD interaction terms (from All Dec. and Sta.V.)

Confirm Model C-1 Alpha=0.05

Dependent Variable: SqrtY

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	20	106.16377	5.30819	48.88	<.0001
Error	68	7.38403	0.10859		
Corrected Total	88	113.54780			

Root MSE	0.32953	R-Square	0.9350
Dependent Mean	3.88088	Adj R-Sq	0.9158
Coeff Var	8.49105		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	2.87966	0.16646	17.30	<.0001	0
mid_osw	1	0.10844	0.00699	15.51	<.0001	2.94575
stp3G9_stdx2	1	-0.67227	0.09730	-6.91	<.0001	1.50934
stp3G9_stdx29	1	0.56297	0.07308	7.70	<.0001	1.57495
std2G2_stdx23	1	0.55400	0.07606	7.28	<.0001	1.31461
std3G3_stdx32	1	-0.30370	0.06182	-4.91	<.0001	1.46429
std3G4_stdx7	1	-0.49691	0.14357	-3.46	0.0009	1.87775
stp2G4_stdx36	1	-0.47553	0.09261	-5.13	<.0001	1.32384
std3G7_stdx26	1	-0.43547	0.08900	-4.89	<.0001	1.32048
stp2G11_stdx46	1	-0.30600	0.05314	-5.76	<.0001	1.49348
stp3G4_stdx5	1	0.39542	0.10330	3.83	0.0003	1.38869
std2G4_stdx40	1	-0.23635	0.04389	-5.38	<.0001	1.48321
std2G1_stdx41	1	-0.18692	0.04749	-3.94	0.0002	1.43796
std2G5_stdx23	1	-0.42295	0.09825	-4.30	<.0001	2.00078
stp2G11_stdx27	1	0.38908	0.09954	3.91	0.0002	1.42803
std2G1_stdx23	1	0.19109	0.06344	3.01	0.0036	1.42455
std2G7_stdx38	1	-0.37288	0.09612	-3.88	0.0002	5.53765
std2G1_stdx3	1	0.34009	0.11284	3.01	0.0036	1.80850
std3G6_stdx28	1	0.47742	0.13648	3.50	0.0008	2.95029
stp2G4_stdx28	1	-0.38374	0.14204	-2.70	0.0087	3.10326
phydx4	1	-0.39091	0.18332	-2.13	0.0366	5.56400

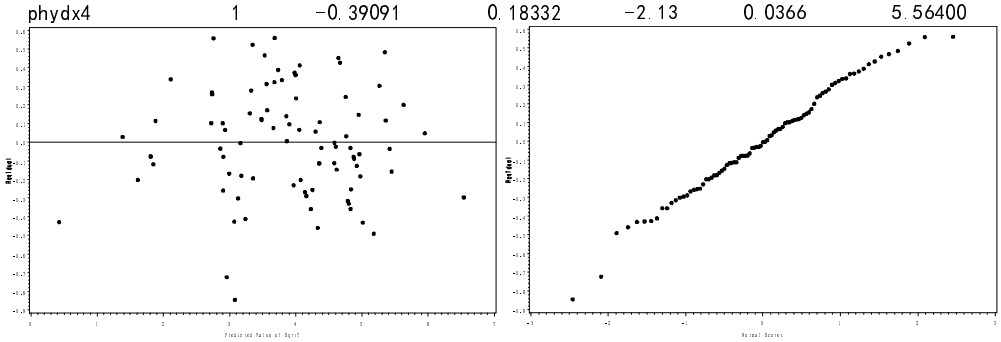


Figure A.35 Model C–1 of PostOSW

✓ Confirm Model C-2 Alpha=0.01 of PostOSW

Dependent Variable: SqrtY

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	92.52013	13.21716	50.91	<.0001
Error	81	21.02767	0.25960		
Corrected Total	88	113.54780			

Root MSE	0.50951	R-Square	0.8148
Dependent Mean	3.88088	Adj R-Sq	0.7988
Coeff Var	13.12872		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	2.54990	0.18268	13.96	<.0001	0
mid_osw	1	0.10504	0.00818	12.84	<.0001	1.68560
stp3G9_stdx2	1	-0.53672	0.14345	-3.74	0.0003	1.37213
stp3G9_stdx29	1	0.42297	0.10340	4.09	0.0001	1.31885
std2G2_stdx23	1	0.49005	0.11065	4.43	<.0001	1.16368
std3G3_stdx32	1	-0.31736	0.08244	-3.85	0.0002	1.08924
std3G4_stdx7	1	-0.67355	0.20603	-3.27	0.0016	1.61755
stp2G4_stdx36	1	-0.38741	0.13454	-2.88	0.0051	1.16854

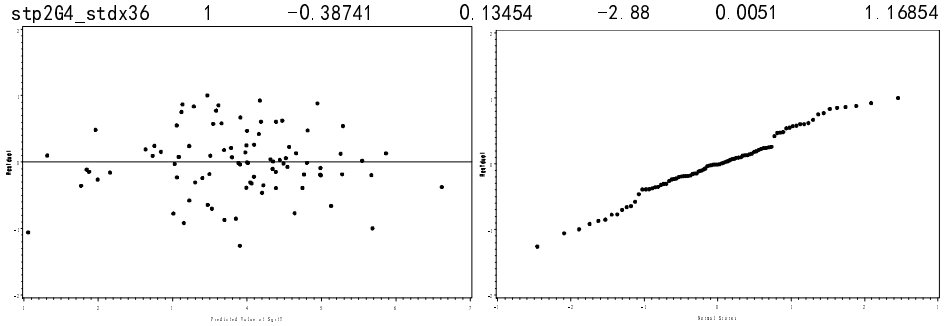


Figure A.36 Model C–2 of PostOSW

✓ Preliminary Model 1 of PostPDA

Confirm P-Model 1 Alpha=0.1

Dependent Variable: post_pda

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	316.38412	22.59887	15.36	<.0001
Error	74	108.85183	1.47097		
Corrected Total	88	425.23596			

Root MSE	1.21284	R-Square	0.7440
Dependent Mean	4.60674	Adj R-Sq	0.6956
Coeff Var	26.32741		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.81794	0.51407	3.54	0.0007	0
mid_osw	1	0.08849	0.02177	4.06	0.0001	2.10781
mid_pda	1	0.32881	0.08094	4.06	0.0001	1.92888
D_2G4	1	0.82574	0.18359	4.50	<.0001	1.85885
D_2G5	1	-0.34900	0.11089	-3.15	0.0024	1.20009
numpt2	1	0.06382	0.03027	2.11	0.0384	1.06640
D_3G3	1	0.91786	0.18464	4.97	<.0001	1.21669
Pr_3G4	1	0.85946	0.35510	2.42	0.0180	1.12307
marital	1	-0.36811	0.14347	-2.57	0.0123	1.09940
children	1	-0.21973	0.08453	-2.60	0.0113	1.10503
phydx3	1	-1.16972	0.46280	-2.53	0.0136	1.29247
phydx4	1	0.92219	0.32083	2.87	0.0053	1.25798
phydxoth	1	1.20283	0.38452	3.13	0.0025	1.11581
D_3G4	1	-0.64567	0.18500	-3.49	0.0008	1.77307
pastdx14	1	-1.51900	0.45809	-3.32	0.0014	1.15408

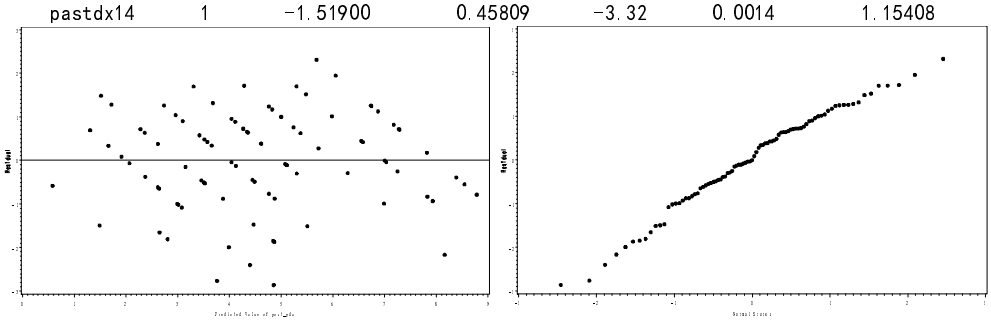


Figure A.37 Preliminary Model 1 of PostPDA

Preliminary Model 2 of PostPDA - SqrtY

Confirm P-Model 2 Alpha=0.1 Dependent Variable: SqrtY

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	24.01040	1.33391	13.11	<.0001
Error	70	7.12258	0.10175		
Corrected Total	88	31.13298			

Root MSE	0.31898	R-Square	0.7712
Dependent Mean	2.06323	Adj R-Sq	0.7124
Coeff Var	15.46042		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.36932	0.12648	10.83	<.0001	0
mid_pda	1	0.06199	0.02193	2.83	0.0061	2.04659
mid_osw	1	0.02620	0.00654	4.01	0.0002	2.75014
pastdx7	1	-0.20255	0.10391	-1.95	0.0553	1.52384
phydx4	1	0.21217	0.09096	2.33	0.0226	1.46182
D_3G3	1	0.11941	0.04951	2.41	0.0185	1.26486
D_2G4	1	0.27760	0.05065	5.48	<.0001	2.04495
D_3G7	1	-0.44295	0.08797	-5.04	<.0001	2.04936
D_2G7	1	0.32125	0.07908	4.06	0.0001	2.09255
phydx3	1	-1.05389	0.25043	-4.21	<.0001	5.47093
D_3G4	1	-0.13495	0.04833	-2.79	0.0067	1.74947
children	1	-0.05126	0.02330	-2.20	0.0311	1.21383
num_grp2	1	0.02190	0.01171	1.87	0.0657	1.32417
numpt2	1	0.01870	0.00818	2.28	0.0253	1.12702
D_2G5	1	-0.08598	0.03094	-2.78	0.0070	1.35056
pastdx3	1	0.76280	0.28448	2.68	0.0091	5.79092
D_3G2	1	-0.08891	0.03942	-2.26	0.0272	1.48289
phydx6	1	-0.17679	0.07519	-2.35	0.0215	1.23484
D_2G1	1	-0.10203	0.05232	-1.95	0.0552	1.31866

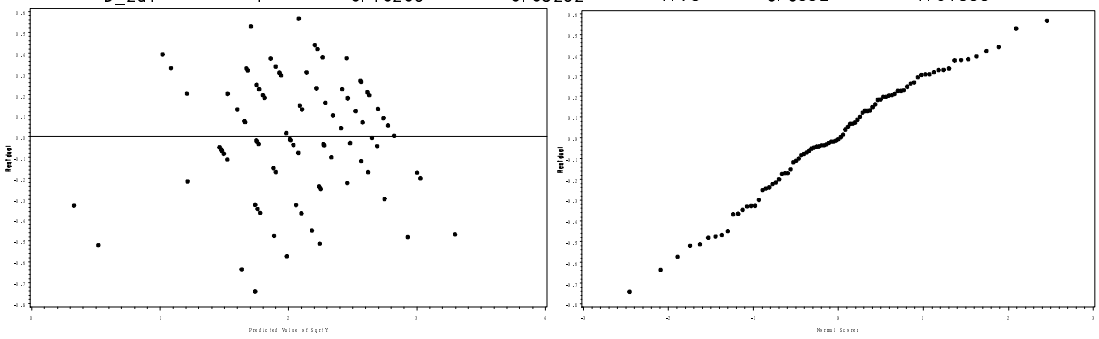


Figure A.38 Preliminary Model 2 of PostPDA

Model A of PostPDA:

PostPDA = all state and decision variables and STD interaction terms (All Dec.and Selected Sta.V.from PostPDA)

Confirm for Model A

Dependent Variable: post_pda

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	368.67871	23.04242	29.33	<.0001
Error	72	56.55724	0.78552		
Corrected Total	88	425.23596			

Root MSE	0.88629	R-Square	0.8670
Dependent Mean	4.60674	Adj R-Sq	0.8374
Coeff Var	19.23907		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	3.30383	0.29685	11.13	<.0001	0
stp2G1_stdx3	1	-2.29681	0.29795	-7.71	<.0001	1.74329
std2G2_stdx30	1	1.20995	0.23560	5.14	<.0001	1.41083
std2G4_stdx46	1	-0.83890	0.10588	-7.92	<.0001	1.19808
std3G3_stdx22	1	-1.58467	0.26340	-6.02	<.0001	1.40850
std2G2_stdx38	1	-0.38522	0.14885	-2.59	0.0117	1.29056
stp2G10_stdx29	1	-0.67712	0.18007	-3.76	0.0003	1.20491
stp3G4_stdx2	1	-1.38580	0.45845	-3.02	0.0035	2.76357
std2G5_stdx37	1	0.99700	0.17708	5.63	<.0001	1.18810
std3G4_stdx53	1	0.53867	0.18336	2.94	0.0044	1.35312
std3G7_stdx22	1	1.18693	0.27141	4.37	<.0001	1.80108
stp3G11_stdx2	1	-1.28182	0.32669	-3.92	0.0002	1.95970
stp2G10_stdx53	1	-0.35636	0.13081	-2.72	0.0081	1.48625
std2G1_stdx2	1	1.40917	0.40089	3.52	0.0008	2.28715
std2G8_stdx30	1	0.48081	0.20139	2.39	0.0196	1.15320
D_2G7	1	0.51270	0.18929	2.71	0.0084	1.55299
D_3G1	1	0.31222	0.12332	2.53	0.0135	1.27602

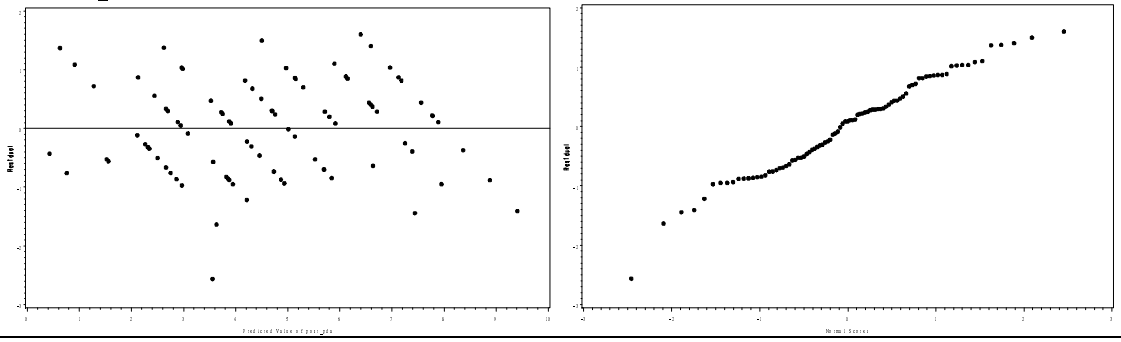


Figure A.39 Model A of PostPDA

Model B of PostPDA:

Post_PDA = selected state and decision variables and STD interaction terms (All Dec. and Selected Sta.V. from Post_PDA)

Confirm for Model B

Dependent Variable: post_pda

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	368.02925	21.64878	26.87	<.0001
Error	71	57.20670	0.80573		
Corrected Total	88	425.23596			

Root MSE	0.89762	R-Square	0.8655
Dependent Mean	4.60674	Adj R-Sq	0.8333
Coeff Var	19.48500		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	3.96219	0.28161	14.07	<.0001	0
stp2G1_stdx3	1	-2.29459	0.31097	-7.38	<.0001	1.85141
std2G2_stdx30	1	1.16827	0.23921	4.88	<.0001	1.41793
std2G4_stdx46	1	-0.86292	0.10741	-8.03	<.0001	1.20218
std3G3_stdx22	1	-1.61409	0.27083	-5.96	<.0001	1.45175
std2G2_stdx38	1	-0.42373	0.15314	-2.77	0.0072	1.33167
stp2G10_stdx29	1	-0.73191	0.18967	-3.86	0.0002	1.30340
stp3G4_stdx2	1	-1.57879	0.45801	-3.45	0.0010	2.68911
std2G5_stdx37	1	0.90143	0.18032	5.00	<.0001	1.20116
std3G4_stdx53	1	0.58636	0.21387	2.74	0.0077	1.79482
std3G7_stdx22	1	1.51290	0.37231	4.06	0.0001	3.30410
stp3G11_stdx2	1	-1.08160	0.32649	-3.31	0.0015	1.90822
stp2G10_stdx53	1	-0.34412	0.13526	-2.54	0.0131	1.54925
std2G1_stdx2	1	1.36278	0.40830	3.34	0.0013	2.31305
std2G8_stdx30	1	1.40854	0.42290	3.33	0.0014	4.95736
std3G1_stdx53	1	-0.31002	0.18163	-1.71	0.0922	1.73298
std3G7_stdx30	1	-1.02912	0.43319	-2.38	0.0202	5.77973
std2G8_stdx22	1	-0.60779	0.34678	-1.75	0.0840	2.31104

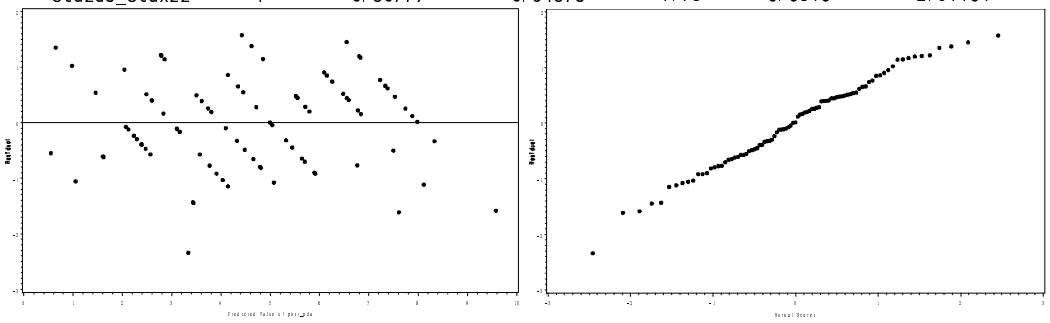


Figure A.40 Model B of PostPDA

Model C of PostPDA:

Post_PDA = ALL state and decision variables and STD interaction terms (from All Dec. and Sta.V.)

Model C with Alpha= 0.1 and 0.05 have R-square =1 and over 100 variables

✓ Confirm Model C Alpha=0.01

Dependent Variable: post_pda

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	350.75806	29.22984	29.83	<.0001
Error	76	74.47789	0.97997		
Corrected Total	88	425.23596			

Root MSE	0.98994	R-Square	0.8249
Dependent Mean	4.60674	Adj R-Sq	0.7972
Coeff Var	21.48884		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	5.80045	0.23967	24.20	<.0001	0
stp2G1_stdx3	1	-2.14224	0.33557	-6.38	<.0001	1.77253
std3G3_stdx42	1	-0.57175	0.20793	-2.75	0.0075	1.28979
std2G4_stdx28	1	1.24853	0.24505	5.09	<.0001	1.10395
stp3G4_stdx2	1	-2.35527	0.39364	-5.98	<.0001	1.63314
stp2G1_stdx51	1	0.92326	0.16713	5.52	<.0001	1.32260
stp2G9_stdx47	1	1.02741	0.16985	6.05	<.0001	2.00842
std2G4_stdx51	1	-0.69908	0.12464	-5.61	<.0001	1.22894
stp2G10_stdx37	1	-0.93632	0.16607	-5.64	<.0001	2.30703
stp2G1_stdx39	1	-1.28855	0.23791	-5.42	<.0001	1.95560
std3G5_stdx23	1	-0.86445	0.19238	-4.49	<.0001	1.35004
std3G4_stdx49	1	0.99954	0.24869	4.02	0.0001	1.72568
std3G5_stdx53	1	0.45457	0.15172	3.00	0.0037	1.34211

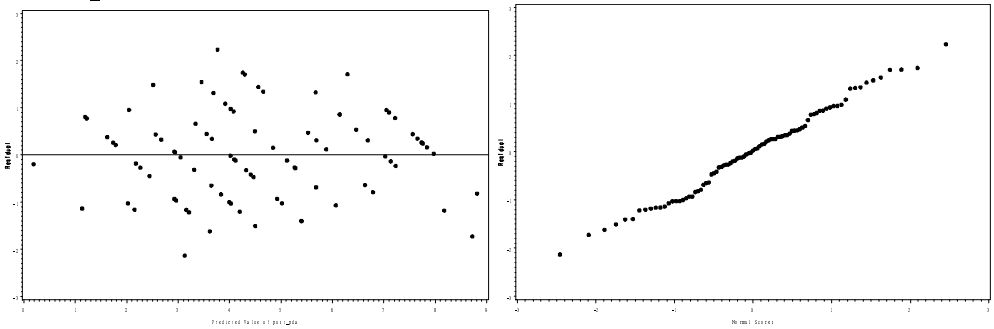


Figure A.41 Model C of PostPDA

Preliminary Model 1 of $NumGr_1$

✓ Confirm Model 1 Alpha=0.1

Dependent Variable: num_grp2

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	9	461.80029	51.31114	7.76	<.0001
Error	81	535.80411	6.61487		
Corrected Total	90	997.60440			

Root MSE	2.57194	R-Square	0.4629
Dependent Mean	3.78022	Adj R-Sq	0.4032
Coeff Var	68.03673		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-9.60951	2.28995	-4.20	<.0001	0
pre_pda	1	0.45552	0.17113	2.66	0.0094	1.20482
txassign	1	1.04251	0.29250	3.56	0.0006	1.19959
pastdx11	1	-1.71455	0.49087	-3.49	0.0008	1.21607
paintype	1	0.93923	0.35556	2.64	0.0099	1.27523
duration	1	0.01549	0.00569	2.72	0.0079	1.33781
D_2G3	1	0.56837	0.28163	2.02	0.0469	1.10260
D_2G5	1	-0.62776	0.23828	-2.63	0.0101	1.24783
S_G2	1	1.96666	0.91239	2.16	0.0341	1.12018
pre_bdi	1	0.05901	0.03408	1.73	0.0871	1.57016

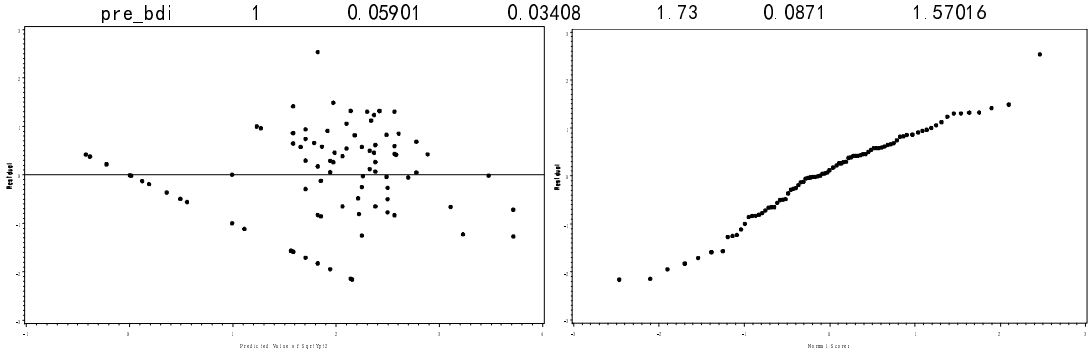


Figure A.42 Preliminary Model 1 of $NumGr_1$

Preliminary Model 2 of $NumGr_1$ Alpha=0.1

Dependent Variable: SqrtYgrp2

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	47.94547	6.84935	7.28	<.0001
Error	83	78.08504	0.94078		
Corrected Total	90	126.03051			

Root MSE	0.96994	R-Square	0.3804
Dependent Mean	1.54767	Adj R-Sq	0.3282
Coeff Var	62.67115		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-2.43624	0.76437	-3.19	0.0020	0
pre_pda	1	0.16155	0.06532	2.47	0.0154	1.23428
txassign	1	0.41704	0.10849	3.84	0.0002	1.16028
phydx9	1	-1.52702	0.64256	-2.38	0.0198	1.27322
pastdx14	1	-0.94302	0.34197	-2.76	0.0072	1.00809
paintype	1	0.34226	0.12565	2.72	0.0079	1.11975
D_2G5	1	-0.17766	0.08371	-2.12	0.0368	1.08290
D_2G3	1	0.19876	0.10400	1.91	0.0594	1.05723

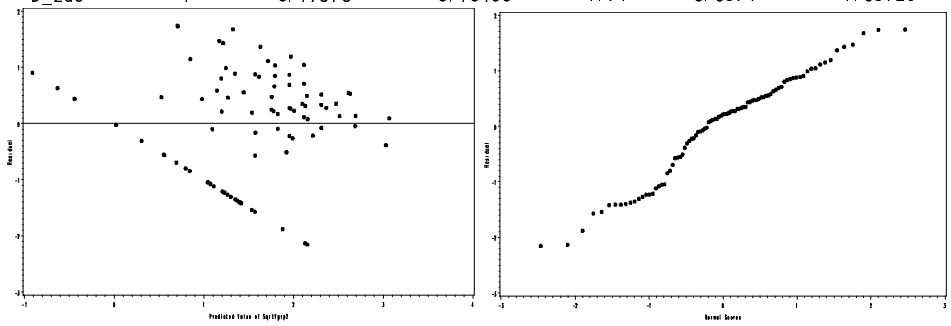


Figure A.43 Preliminary Model 2 of $NumGr_1$

Model A of $NumGr_1$ Alpha=0.1

Dependent Variable: num_grp2

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	10	590.14501	59.01450	11.59	<.0001
Error	80	407.45939	5.09324		
Corrected Total	90	997.60440			

Root MSE	2.25682	R-Square	0.5916
Dependent Mean	3.78022	Adj R-Sq	0.5405
Coeff Var	59.70080		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-0.36107	1.42502	-0.25	0.8006	0
std2G5_stdx5	1	-3.17916	0.70232	-4.53	<.0001	1.12407
std2G3_stdx6	1	-2.95056	0.60580	-4.87	<.0001	1.06934
std2G7_stdx26	1	-1.56114	0.59261	-2.63	0.0101	1.12428
txassign	1	0.88447	0.24877	3.56	0.0006	1.12696
std2G1_stdx52	1	3.17942	0.64251	4.95	<.0001	4.84358
std2G1_stdx4	1	-3.25690	0.82592	-3.94	0.0002	3.86643
stp2G4_stdx4	1	-1.83436	0.77508	-2.37	0.0204	1.03294
phydx11	1	1.61891	0.59134	2.74	0.0076	2.52294
S_G2	1	1.57014	0.77607	2.02	0.0464	1.05256
std2G6_stdx52	1	0.83078	0.43497	1.91	0.0597	1.79858

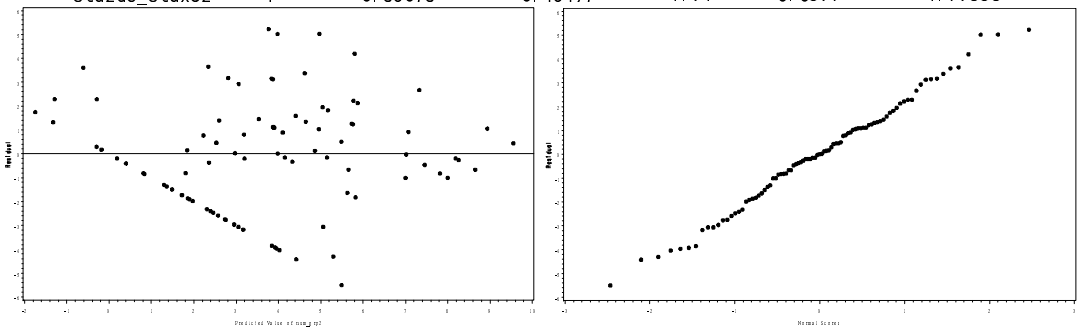


Figure A.44 Model A of $NumGr_1$

Model B of $NumGr_1$ Alpha=0.1

Dependent Variable: num_grp2

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	8	525.44984	65.68123	11.41	<.0001
Error	82	472.15455	5.75798		
Corrected Total	90	997.60440			

Root MSE	2.39958	R-Square	0.5267
Dependent Mean	3.78022	Adj R-Sq	0.4805
Coeff Var	63.47725		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	3.36442	0.95945	3.51	0.0007	0
std2G5_stdx5	1	-3.32788	0.72097	-4.62	<.0001	1.04779
std2G3_stdx6	1	-3.05141	0.63564	-4.80	<.0001	1.04136
std2G7_stdx26	1	-1.51496	0.61375	-2.47	0.0157	1.06669
std2G1_stdx52	1	2.27961	0.43932	5.19	<.0001	2.00303
std2G1_stdx27	1	-2.41649	0.64190	-3.76	0.0003	2.01717
stp2G4_stdx4	1	-1.73830	0.83851	-2.07	0.0413	1.06935
S_G2	1	2.07113	0.83467	2.48	0.0151	1.07697
duration	1	0.00960	0.00494	1.94	0.0557	1.16157

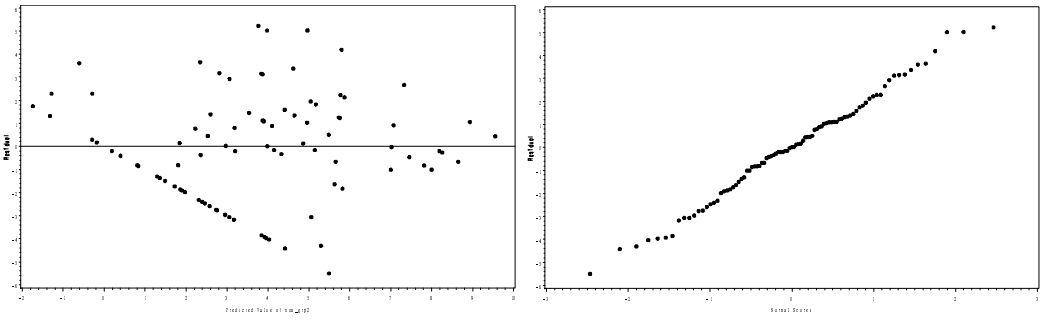


Figure A.45 Model B of $NumGr_1$

Model C of $NumGr_1$ Alpha=0.05648

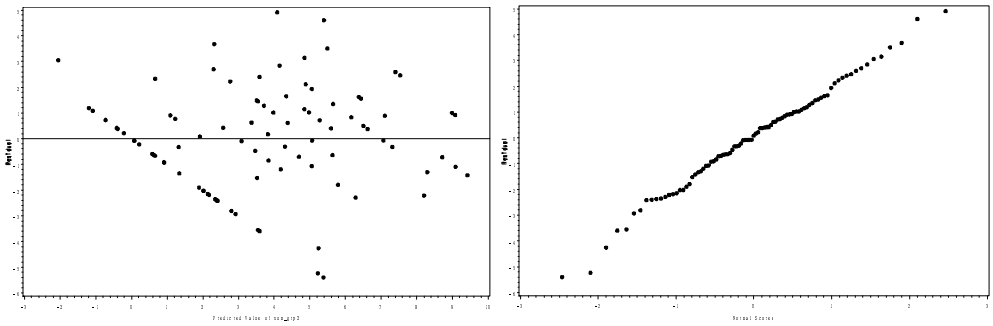
Dependent Variable: num_grp2

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	10	634.83349	63.48335	14.00	<.0001
Error	80	362.77090	4.53464		
Corrected Total	90	997.60440			

Root MSE	2.12947	R-Square	0.6364
Dependent Mean	3.78022	Adj R-Sq	0.5909
Coeff Var	56.33187		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-3.27621	1.42295	-2.30	0.0239	0
std2G5_stdx5	1	-3.04455	0.67681	-4.50	<.0001	1.17249
std2G3_stdx6	1	-2.93476	0.63244	-4.64	<.0001	1.30905
stp2G1_stdx26	1	-2.19403	0.64873	-3.38	0.0011	1.21206
txassign	1	0.74439	0.22962	3.24	0.0017	1.07837
duration	1	0.01524	0.00442	3.45	0.0009	1.18035
std2G1_stdx32	1	-1.23893	0.35209	-3.52	0.0007	1.92503
std2G1_stdx52	1	2.00549	0.38960	5.15	<.0001	2.00029
std2G4_stdx40	1	0.95465	0.24924	3.83	0.0003	1.17266
std2G7_stdx42	1	1.35083	0.47633	2.84	0.0058	1.40172
std2G5_stdx53	1	0.99921	0.43245	2.31	0.0234	1.30737



Model C of Num_grp2 Alpha=0.01

All variables left in the model are significant at the 0.0100 level. No other variable met the 0.0100 significance level for entry into the model.

Summary of Stepwise Selection

Step	Variable Entered	Variable Removed	Number Vars In	Partial R-Square	Model R-Square	C(p)	F Value	Pr > F
1	std2G5_stdx5		1	0.1490	0.1490	.	15.58	0.0002
2	std2G3_stdx6		2	0.1179	0.2669	.	14.15	0.0003
3	std2G7_stdx53		3	0.0843	0.3511	.	11.30	0.0012
4	stp2G1_stdx26		4	0.0521	0.4032	.	7.51	0.0075

Figure A.46 Model C of $NumGr_1$

Preliminary Model 1 of Num_pt2 Alpha=0.1

Dependent Variable: numpt2

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	691.82286	115.30381	9.12	<.0001
Error	84	1061.78154	12.64026		
Corrected Total	90	1753.60440			

Root MSE	3.55531	R-Square	0.3945
Dependent Mean	5.21978	Adj R-Sq	0.3513
Coeff Var	68.11233		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	-0.03777	1.43032	-0.03	0.9790	0
Pr_2G10	1	6.26307	1.13868	5.50	<.0001	1.85989
Pr_2G9	1	-4.08416	1.29110	-3.16	0.0022	1.82306
phydx8	1	5.16497	1.88169	2.74	0.0074	1.07122
onset	1	0.00857	0.00282	3.04	0.0032	1.09456
pre_osw	1	0.11826	0.04168	2.84	0.0057	1.10093
phydx5	1	2.48207	1.21015	2.05	0.0434	1.03126

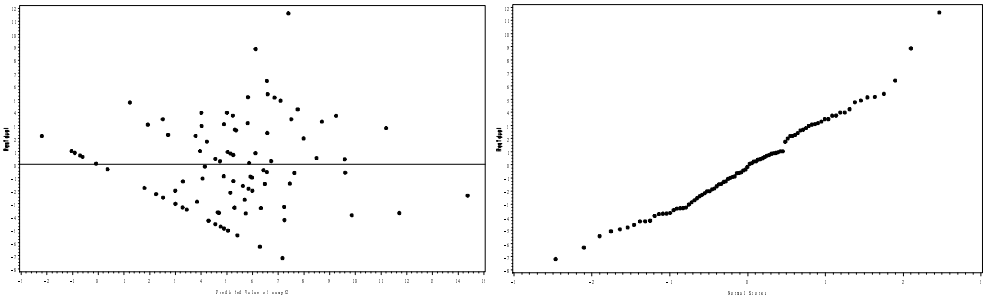


Figure A.47 Preliminary Model 1 of $NumPT_1$

✓ Preliminary Model 1 of $NumPT_2$ – SqrtY Alpha=0.1

Dependent Variable: SqrtYpt2

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	62.07563	10.34594	10.75	<.0001
Error	84	80.84216	0.96241		
Corrected Total	90	142.91779			

Root MSE	0.98102	R-Square	0.4343
Dependent Mean	1.91030	Adj R-Sq	0.3939
Coeff Var	51.35435		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.99401	0.29468	3.37	0.0011	0
Pr_2G10	1	2.48255	0.32358	7.67	<.0001	1.97266
Pr_2G9	1	-1.89105	0.36656	-5.16	<.0001	1.93011
pastdx7	1	0.74104	0.26713	2.77	0.0068	1.07064
D_2G3	1	0.27820	0.11089	2.51	0.0140	1.17489
D_2G1	1	0.33193	0.13978	2.37	0.0198	1.13600
children	1	0.11918	0.06771	1.76	0.0820	1.11319

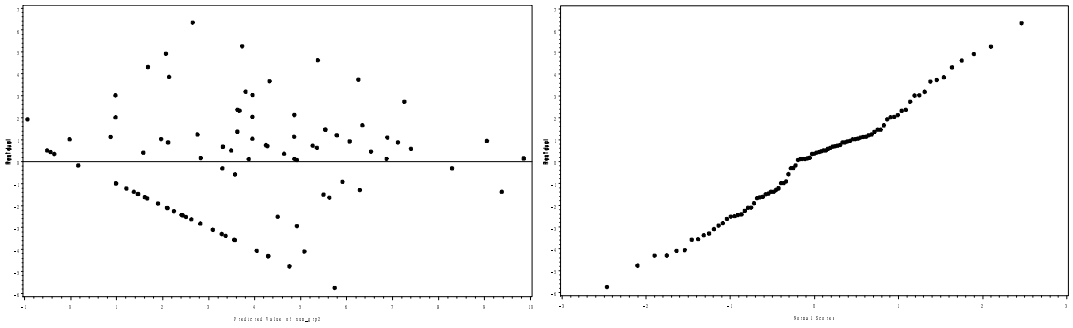


Figure A.48 Preliminary Model 2 of $NumPT_1$

Model A of $NumPT_1$

Dependent Variable: SqrtYpt2

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	67.66379	11.27730	12.59	<.0001
Error	84	75.25400	0.89588		
Corrected Total	90	142.91779			

Root MSE	0.94651	R-Square	0.4734
Dependent Mean	1.91030	Adj R-Sq	0.4358
Coeff Var	49.54765		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.81930	0.24416	7.45	<.0001	0
Pr_2G10	1	2.33965	0.30364	7.71	<.0001	1.86600
Pr_2G9	1	-1.73740	0.34536	-5.03	<.0001	1.84045
std2G6_stdx51	1	-0.38691	0.11170	-3.46	0.0008	1.00860
std2G1_stdx30	1	-0.46875	0.15814	-2.96	0.0039	1.05322
D_2G3	1	0.20962	0.10412	2.01	0.0473	1.11265
D_2G8	1	-0.84165	0.49193	-1.71	0.0908	1.03300

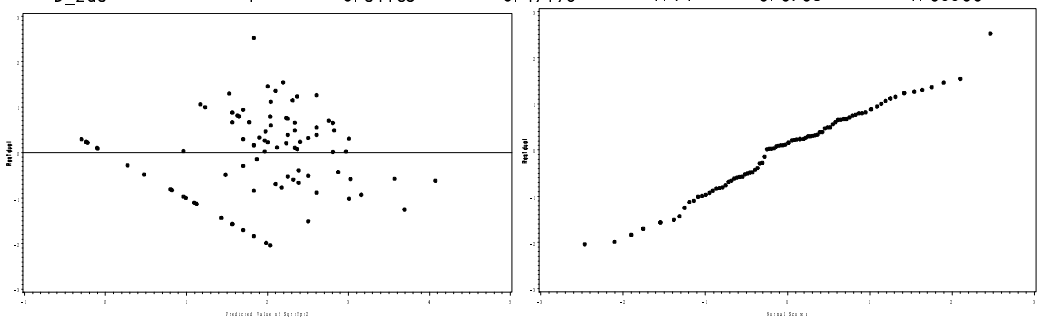


Figure A.49 Model A of $NumPT_1$

Model B of Num PT_1

Dependent Variable: SqrtYpt2

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	65.04135	13.00827	14.20	<.0001
Error	85	77.87644	0.91619		
Corrected Total	90	142.91779			

Root MSE	0.95718	R-Square	0.4551
Dependent Mean	1.91030	Adj R-Sq	0.4230
Coeff Var	50.10620		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.81357	0.24689	7.35	<.0001	0
Pr_2G10	1	2.30863	0.30652	7.53	<.0001	1.85935
Pr_2G9	1	-1.76225	0.34894	-5.05	<.0001	1.83719
std2G6_stdx51	1	-0.38989	0.11295	-3.45	0.0009	1.00835
std2G1_stdx30	1	-0.46597	0.15991	-2.91	0.0046	1.05310
D_2G3	1	0.23001	0.10460	2.20	0.0306	1.09807

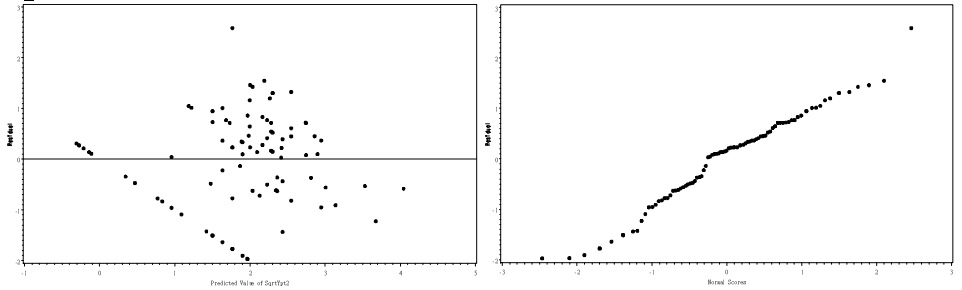


Figure A.50 Model B of NumPT_1

✓ Model C of Num PT_1 Alpha=0.03 Dependent Variable: SqrtYpt2

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	120.77932	7.10467	23.43	<.0001
Error	73	22.13847	0.30327		
Corrected Total	90	142.91779			

Root MSE	0.55070	R-Square	0.8451
Dependent Mean	1.91030	Adj R-Sq	0.8090
Coeff Var	28.82772		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	3.59715	0.32770	10.98	<.0001	0
Pr_2G10	1	3.86230	0.29630	13.04	<.0001	5.24900
stp2G9_stdx42	1	1.36852	0.10883	12.57	<.0001	2.34840
std2G5_stdx6	1	-3.69775	0.29267	-12.63	<.0001	3.00701
stp2G4_stdx25	1	-0.80363	0.14766	-5.44	<.0001	1.54634
stp2G10_stdx54	1	0.69670	0.13961	4.99	<.0001	4.66113
std2G5_stdx29	1	1.46811	0.28868	5.09	<.0001	3.18534
std2G7_stdx29	1	-0.95879	0.20074	-4.78	<.0001	2.54653
pre_bdi	1	-0.09369	0.01067	-8.78	<.0001	3.35741
std2G1_stdx6	1	-0.96545	0.16170	-5.97	<.0001	1.94032
std2G8_stdx33	1	0.39579	0.08649	4.58	<.0001	1.16874
std2G6_stdx52	1	-0.51598	0.09471	-5.45	<.0001	1.43219
std2G5_stdx46	1	0.84475	0.15407	5.48	<.0001	2.52673
stp2G10_stdx7	1	0.77082	0.15308	5.04	<.0001	1.21918
pastdx5	1	-0.98650	0.24642	-4.00	0.0001	1.46102
stp2G11_stdx30	1	-0.40657	0.11683	-3.48	0.0009	1.13534
std2G5_stdx37	1	-0.38015	0.14070	-2.70	0.0086	1.97079
std2G7_stdx43	1	-0.31927	0.13272	-2.41	0.0187	1.44842

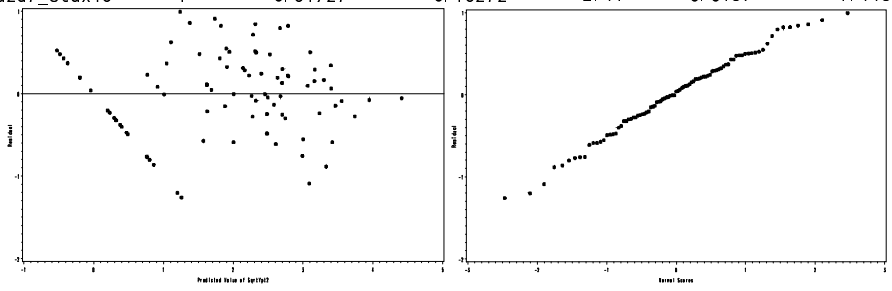


Figure A.51 Model C of $NumPT_1$

APPENDIX B

RE-OPTIMIZATION RESULTS

Table B.1 The Notations of Selected Treatments in BDI Model

u in the 1st stage												
u1	u2	u3	u4	u5	u6	u7	u8	u9	u10	u11	u12	u13
$RxGr3_1$	$RxGr5_1$	$ProcGr9_1$	$ProcGr4_1$	$RxGr2_1$	$RxGr8_1$	$RxGr4_1$	$RxGr6_1$	$ProcGr1_1$	$RxGr7_1$	$ProcGr10_1$	$RxGr1_1$	$ProcGr11_1$
u in the 2nd stage												
u1	u2	u3	u4	u5	u6							
$RxGr7_2$	$ProcGr9_2$	$ProcGr11_2$	$RxGr2_2$	$RxGr5_2$	$ProcGr4_2$							

Table B.2 SDP Re-optimization Result of BDI Model

	Pre	u in the 1st stage (from SDP re-optimization)													MidBDI			u in the 2nd stage						PostBDI				
	BDI	1	2	3	4	5	6	7	8	9	10	11	12	13	TU	SDP	Orig.	1	2	3	4	5	6	TU	StD	SDP	StD	Orig.
1	46	3.1	5	0.4	1.5	0	0.6	1	0	1.7	0.6	0.2	0	0	14	21.51	50	0.2	0	0	0.1	0	0.1	0.40	0.05	10.86	0.06	46
2	34	0	1.6	0	1	0.6	0	0.2	0	0	0.4	0	0	0	3.8	15.07	25	0	0	0	0	0	0	0	0	5.68	1.00	34
3	4	0	1.4	0	0	0	0	0	0	0	0.3	0	0.1	0	1.8	0.32	4	0	0	0	0	0	0	0	0	2.03	0.37	6
4	6	0.1	2.1	0	0	0	0	0	0	0	0.2	0	0	0	2.4	4.22	6	0	0	0	0	0	0	0	0	1.08	0.33	0
5	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2.43	1	0	0	0	0	0	0	0	0	1.19	0.45	12
6	18	0.5	0	0	0.1	0.2	0	0	0.5	0	0.4	0.2	0	0	2	11.83	16	0	0	0	0	0	0	0	0	0.04	0.06	1
7	20	0	0.5	0	1.3	0.8	0.1	0.3	0	0.6	1	0	0	0	4.6	15.80	20	0	0	0	0	0	0	0	0	1.81	0.54	21
8	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4.10	10	0	0	0	0	0	0	0	0	1.60	0.53	9
9	9	0	1.6	0	0	0	0	0	0	0	0	0	0	0	1.6	6.43	9	0	0	0	0	0	0	0	0	0.24	0.18	1
10	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9.41	11	0	0	0	0	0	0	0	0	4.16	0.82	21
11	31	0	0.3	0	0.6	0	0	0	0	0	0.5	0	0	0	1.4	14.43	31	0	0	0	0	0	0	0	0	8.63	1.18	35
12	18	0.3	0	0	0.1	0.1	0	0	0	0	0.1	0	0	0	0.7	10.39	19	0	0	0	0	0	0	0	0	5.23	0.96	10
13	11	0	0	0	0	0	0	0	0	0	0.1	0	0	0	0.1	3.96	9	0	0	0	0	0	0	0	0	3.15	0.74	3
14	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.19	7	0	0	0	0	0	0	0	0	0.09	0.11	2
15	28	0	1.4	0	0.9	0.5	0	0.1	0	0.5	0.8	0	0	0	4.2	14.46	31	0	0	0	0	0	0	0	0	4.68	0.91	16

Table B.2 – *Continued*

16	33	0	1.8	0	1.2	0.7	0	0.3	0	0	0.5	0	0	0	4.4	15.64	18	0	0	0	0	0	0	0	0	0.57	0.31	21
17	5	0	0.3	0	0	0	0	0	0	0	0	0	0	0	0.3	8.25	4	0	0	0	0	0	0	0	0	2.45	0.61	7
18	20	0	0.2	0	0	0	0	0	0	0	0	0	0	0	0.2	9.98	16	0	0	0	0	0	0	0	0	2.49	0.66	16
19	40	0	0	0	1.1	0.7	0	0.2	1	0	0.4	0	0	0	3.4	15.36	27	0	0	0	0	0	0	0	0	6.75	1.09	4
20	12	0	0.4	0	0	0	0	0	0	0	0.1	0	0	0	0.5	7.19	9	0	0	0	0	0	0	0	0	1.33	0.43	10
21	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5.50	5	0	0	0	0	0	0	0	0	0.28	0.21	5
22	18	0.2	0	0	0.1	0	0	0	0	0	0	0	0	0	0.3	5.60	15	0	0	0	0	0	0	0	0	1.97	0.58	18
23	4	0	0	0	0.1	0	0	0	0	0	0.6	0	0.2	0	0.8	2.15	4	0	0	0	0	0	0	0	0	0.01	0.03	2
24	7	0	0.3	0	0	0	0	0	0	0.4	0	0	0	0	0.7	6.10	2	0	0	0	0	0	0	0	0	0.19	0.11	1
25	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5.12	6	0	0	0	0	0	0	0	0	1.81	0.47	4
26	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.59	25	0	0	0	0	0	0	0	0	1.89	0.57	22
27	21	0	0.1	0	0	0	0	0	0	0	0	0	0	0	0.1	9.65	18	0	0	0	0	0	0	0	0	2.74	0.69	17
28	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3.41	2	0	0	0	0	0	0	0	0	0.93	0.18	1
29	5	1.2	0	0.1	0	0	0	0	0	0	0	0	0	0	1.3	4.51	3	0	0	0	0	0	0	0	0	1.33	0.48	4
30	21	1.1	0	0	1	0	0	0.8	0	0.4	1.1	0	0	0	4.3	13.39	19	0	0	0	0	0	0	0	0	5.43	0.97	15
31	11	0	0.4	0	0	0	0	0	0	0	0	0	0	0	0.4	1.29	6	0	0	0	0	0	0	0	0	2.78	0.40	7
32	5	1.5	0	0.1	0	0	0	0	0	0	0	0	0	0	1.5	6.34	6	0	0	0	0	0	0	0	0	5.22	0.95	6
33	9	0.7	0	0.1	0	0	0	0	0	0	0	0	0	0	0.8	7.63	10	0	0	0	0	0	0	0	0	2.80	0.70	8
34	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7.89	6	0	0	0	0	0	0	0	0	4.40	0.88	10
35	11	0	0.6	0	0	0	0	0	0	0	0.2	0	0	0	0.8	6.39	9	0	0	0	0	0	0	0	0	6.34	0.50	20
36	13	0.1	2.2	0	0.1	0	0	0	0	0	0.3	0	0	0	2.7	7.95	13	0	0	0	0	0	0	0	0	4.73	0.86	17
37	9	0.2	0.8	0	0	0	0	0	0	0	0	0	0	0	1	1.53	10	0	0	0	0	0	0	0	0	2.14	0.53	12
38	6	0	1.3	0	0	0	0	0	0	0	0.3	0.1	0.1	0	1.8	1.03	13	0	0	0	0	0	0	0	0	1.94	0.48	11
39	36	0	1.9	0	0.6	0.8	0	0	0	0	0.8	0	0	0	4.1	15.80	31	0	0	0	0	0	0	0	0	7.06	1.11	27
40	26	0	1.1	0	0.3	0	0	0.1	0	0	0.6	0	0	0	2.1	13.90	25	0	0	0	0	0	0	0	0	6.47	0.63	19
41	16	0	0	0	0	0	0	0	0	0	0.1	0	0	0	0.1	10.35	12	0	0	0	0	0	0	0	0	3.43	0.76	12
42	11	0	0	0	0	0	0	0	0	0	0.1	0	0	0	0.1	3.87	18	0	0	0	0	0	0	0	0	2.74	0.70	15
43	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.23	0	0	0	0	0	0	0	0	0	1.60	0.30	0

Table B.2 – *Continued*

44	16	0	0	0	0	0	0	0	0	0	0	0	0	0	6.06	7	0	0	0	0	0	0	0	5.16	0.90	8
45	10	0	0.6	0	0	0	0	0	0	0	0.2	0	0	0	0.8	0.52	5	0	0	0	0	0	0	0	2.14	0.52	5
46	15	0	0.1	0	0	0	0	0	0	0	0	0	0	0	0.1	11.10	8	0	0	0	0	0	0	0	3.40	0.77	5
47	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5.14	1	0	0	0	0	0	0	0	2.43	0.64	0
48	11	0	1.9	0	0.1	0	0	0	0	0	0.7	0	0	0	2.7	6.57	19	0	0	0	0	0	0	0	2.80	0.60	11
49	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5.25	5	0	0	0	0	0	0	0	4.93	0.93	2
50	20	0	0.6	0	0.3	0	0	0	0	0	0.4	0	0	0	1.2	11.52	9	0	0	0	0	0	0	0	5.61	0.97	9
51	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7.97	10	0	0	0	0	0	0	0	2.01	0.60	11
52	0	0	0.7	0	0	0	0	0	0	0	0.2	0	0	0	1	0.00	0	0	0	0	0	0	0	0	0.05	0.03	1
53	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.57	9	0	0	0	0	0	0	0	2.46	0.22	6
54	39	0	0.4	0	1.4	0	0	0.2	0	0.8	0.8	0	0	0	3.7	16.12	17	0	0	0	0	0	0	0	4.57	0.90	8
55	12	0	0.7	0	0	0	0	0	0	0	0.1	0	0	0	0.8	4.17	17	0	0	0	0	0	0	0	1.14	0.38	1
56	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8.99	1	0	0	0	0	0	0	0	1.98	0.49	4
57	11	0	0	0	0	0	0	0	0.2	0	0.4	0	0	0	0.6	8.44	3	0	0	0	0	0	0	0	0.21	0.18	1
58	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3.82	12	0	0	0	0	0	0	0	0.35	0.21	2
59	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4.21	11	0	0	0	0	0	0	0	2.42	0.58	2
60	21	0	2.5	0	0.1	0	0	0	0	0	0	0	0	0	2.6	11.85	23	0	0	0	0	0	0	0	1.84	0.56	16
61	5	0	0.2	0	0	0	0	0	0	0	0	0	0	0	0.2	0.00	0	0	0	0	0	0	0	0	2.44	0.40	1
62	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3.41	0	0	0	0	0	0	0	0	0.72	0.32	0
63	32	0	0	0	0.9	0	0	0.2	0.8	0	0.4	0	0	0	2.3	14.66	34	0	0	0	0	0	0	0	6.29	0.99	15
64	30	0	0	0	0.6	0	0	0	0.5	0.3	0.5	0	0	0	1.9	13.54	38	0	0	0	0	0	0	0	2.58	0.67	24
65	27	0	1.2	0	0.1	0	0	0	0.3	0	0.2	0	0	0	1.8	12.83	19	0	0	0	0	0	0	0	8.70	1.01	9
66	11	0.1	2.9	0	0.1	0	0	0	0.2	0	0	0	0	0	3.3	10.47	17	0	0	0	0	0	0	0	4.28	0.86	9
67	11	0.1	1.2	0	0	0	0	0	0	0	0.1	0	0	0	1.4	5.23	4	0	0	0	0	0	0	0	2.04	0.58	6
68	18	0	1.4	0	0	0	0	0	0	0	0	0	0	0	1.4	10.44	9	0	0	0	0	0	0	0	3.32	0.77	3
69	7	1.3	0	0	0	0	0	0	0	0	0	0	0	0	1.3	4.71	3	0	0	0	0	0	0	0	2.37	0.65	10
70	6	0	0	0	0.3	0	0	0	0	0	1	0	0	0	1.3	0.13	6	0	0	0	0	0	0	0	1.62	0.43	6
71	10	0	0.2	0	0	0	0	0	0	0	0	0	0	0	0.2	3.93	6	0	0	0	0	0	0	0	3.69	0.79	7

Table B.2 – *Continued*

72	7	0	0.6	0	0	0	0	0	0	0	0	0	0	0	0.6	1.22	5	0	0	0	0	0	0	0	0	1.39	0.49	0
73	4	0	2.7	0	0	0	0	0	0	0	0	0	0	0	2.7	0.10	0	0	0	0	0	0	0	0	0	2.03	0.38	4
74	3	0.3	0	0	0	0	0	0	0	0	0	0	0	0	0.3	1.92	2	0	0	0	0	0	0	0	0	0.42	0.26	4
75	4	1.4	0	0.2	0	0	0	0	0	0	0	0	0	0	1.6	1.34	2	0	0	0	0	0	0	0	0	1.04	0.42	2
76	24	0	0.1	0	0	0	0	0	0	0	0	0	0	0	0.1	11.03	2	0	0	0	0	0	0	0	0	3.02	0.73	2
77	12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4.25	4	0	0	0	0	0	0	0	0	2.02	0.58	7
78	2	0.4	0	0	0	0	0	0	0	0	0	0	0	0	0.4	1.35	0	0	0	0	0	0	0	0	0	0.16	0.16	0
79	7	0	0.5	0	0	0	0	0	0	0	0	0	0	0	0.5	1.40	3	0	0	0	0	0	0	0	0	0.69	0.30	0
80	3	0	2.8	0	0	0	0	0	0	0	0.2	0	0.2	0	3.3	0.01	1	0	0	0	0	0	0	0	0	0.86	0.17	0
81	16	0.5	0	0	0	0	0	0	0	0.1	0.5	0	0	0	1.1	9.82	12	0	0	0	0	0	0	0	0	2.89	0.60	7
82	14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2.25	12	0	0	0	0	0	0	0	0	2.21	0.61	14
83	14	0	0.3	0	0	0	0	0	0	0	0	0	0	0	0.3	10.14	4	0	0	0	0	0	0	0	0	0.24	0.20	0
84	7	0	2.2	0	0	0	0	0	0	0	0.2	0	0	0	2.4	1.84	2	0	0	0	0	0	0	0	0	3.65	0.75	4
85	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2.30	6	0	0	0	0	0	0	0	0	2.83	0.70	8
86	4	0	0	0.1	0	0	0	0	0	0	0	0	0	0	0.1	0.00	2	0	0	0	0	0	0	0	0	1.15	0.22	0
87	29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8.65	12	0	0	0	0	0	0	0	0	2.88	0.71	8
88	13	0	0.8	0	0	0	0	0	0	0	0	0	0	0	0.8	8.36	11	0	0	0	0	0	0	0	0	2.43	0.64	15
89	12	0	0.8	0	0	0	0	0	0	0	0.4	0	0	0	1.2	8.24	6	0	0	0	0	0	0	0	0	1.37	0.44	6

Table B.3 The Notations of Selected Treatments in OSW Model

u in the 1st stage									
u1	u2	u3	u4	u5	u6	u7	u8	u9	u10
$ProcGr1_1$	$RxGr8_1$	$RxGr7_1$	$ProcGr9_1$	$ProcGr4_1$	$RxGr2_1$	$RxGr5_1$	$RxGr3_1$	$RxGr1_1$	$RxGr4_1$
u in the 2nd stage									
u1	u2	u3							
$ProcGr9_2$	$RxGr3_2$	$RxGr4_2$							

Table B.4 SDP Re-optimization Result of OSW Model

	Pre	u in the 1st stage (from SDP re-optimization)										MidOSW			u in the 2nd stage			PostOSW				
	OSW	1	2	3	4	5	6	7	8	9	10	TU	SDP	Orig.	1	2	3	TU	StD	SDP	StD	Orig.
1	22	0	0.1	0	0	0	0	0	0.2	0	0	0.3	13.40	29	0	0	0	0	0	9.85	1.39	29
2	35	2.2	0.3	0	0	0.4	0	0.8	0	0	0	3.6	12.47	35	0	0	0	0	0	9.94	1.40	39
3	22	0	0	0	0	0.6	0	0.1	0	0	0	0.8	8.94	13	0	0	0	0	0	9.92	1.14	8
4	29	2.3	0	0	0	1.3	0	0	2.9	0	0	6.5	5.19	14	0	0	0	0	0	5.97	1.08	13
5	20	0	0	0.1	0	0	0	0	0	0	0	0.1	13.51	19	0	0	0	0	0	9.45	1.35	21
6	30	0	0	0	0	0	0.2	0	0	0	0	0.2	12.26	14	0	0	0	0	0	10.97	1.32	8
7	6	0	0	0	0	0	0	0	0	0	0	0.0	0.00	6	0	0	0	0	0	0.88	0.37	8
8	31	2	0	1.1	0	0.7	0	0	0	0	0	3.7	20.38	33	0.004	1.074	0.283	1.361	0.38	21.80	1.44	30
9	17	0.7	0.2	0.5	0	0.6	0.5	0	0.4	0	0	2.9	10.85	21	0	0	0	0	0	5.58	0.72	17
10	29	1.8	0	0	0	1.1	0	0.4	0	0	0	3.4	13.05	26	0	0	0.009	0.009	0.02	18.30	1.59	20
11	3	0	0.3	0	0	0.6	0.7	0	0	0	0	1.7	5.08	16	0	0	0	0	0	3.03	0.44	16
12	26	0.1	0	0	0	0.3	0	0	0.9	0	0	1.3	16.41	25	0	0	0	0	0	13.51	1.63	20
13	39	1.8	0	0	0	0.1	0	0	0	0	0	1.9	12.64	28	0	0	0.003	0.003	0.02	12.51	1.55	21
14	14	0	0	0	0	0	0	0	0	0	0	0.0	13.14	17	0	0.011	0	0.011	0.04	13.14	1.53	14
15	20	0	0	0	0	0.2	0	0	0	0	0	0.2	14.39	28	0	0	0	0	0	7.99	1.25	7
16	25	0	0	0	0	0	0	0	0	0	0	0.0	13.04	16	0	0	0	0	0	6.29	1.11	18
17	20	0	0	0.6	0.3	0.4	0	0	0	0	0	1.4	16.58	17	0	0.63	0	0.63	0.22	19.24	1.38	16
18	24	0	0	0	0.2	0.6	0	0	0	0	0	0.8	19.68	24	0	0	0	0	0	16.66	1.81	20
19	25	0	0.5	0	0	0.3	0	0	0	0	0	0.9	17.16	25	0	0	0	0	0	6.73	1.15	14
20	9	0	0	0	0	0.4	0.8	0	0	0	0	1.1	7.17	6	0	0	0	0	0	4.92	0.52	4
21	27	0	0	0	0	0	0	0	0	0	0	0.0	15.30	14	0	0	0	0	0	11.10	1.45	7
22	29	1.3	0	1	0	0.7	0	0	2	0	0	5.1	18.30	26	0	0	0	0	0	13.53	1.61	23
23	4	0.5	0	0	0	0	0.4	0.3	0.4	0	0	1.6	9.32	3	0	0	0	0	0	5.89	0.55	3
24	5	0.2	0	0.1	0	0	0.6	0	0	0	0	1.0	4.72	0	0	0	0	0	0	3.21	0.37	0

Table B.4 – *Continued*

25	17	0.2	0	0	0	0	0.5	0	0.3	0	0	1.0	8.81	3	0	0	0	0	0	7.27	0.76	6
26	25	0	0	0.6	0	0.3	0	0	0	0	0	0.9	16.69	25	0	0.437	0	0.437	0.22	18.01	1.47	26
27	24	0	0	0	0	0.2	0	0	0	0	0	0.2	15.80	25	0	0	0	0	0	10.80	1.45	23
28	17	0	0	0	0	0	0	0	0.3	0	0	0.3	13.28	16	0	0	0	0	0	11.78	0.86	15
29	13	0	0	0	0	0.9	0.3	1.9	0	0.2	0.1	3.4	2.37	16	0	0	0	0	0	4.01	0.70	11
30	15	0	0	0	0	0.1	0.1	0	0	0	0	0.2	13.09	20	0	0	0	0	0	6.85	1.05	20
31	20	0	0.1	0	0	0.1	0.7	0	0.2	0	0	1.2	2.98	9	0	0	0	0	0	4.16	0.35	15
32	16	0.1	0	0	0	0	0.1	0	0.1	0	0	0.3	11.28	10	0	0	0	0	0	7.06	1.02	9
33	15	0	0	0	0	0	0	0	0	0	0	0.0	13.81	13	0	0.001	0	0.001	0.01	11.63	1.50	19
34	11	0	0	0	0	0	0	0	0	0	0	0.0	5.20	14	0	0	0	0	0	2.96	0.76	10
35	19	0	0	0	0	0.1	0.5	0	0.2	0	0	0.8	10.86	13	0	0	0	0	0	10.04	0.61	17
36	22	0	0	0	0	0.5	0	0	1.5	0	0	1.9	16.27	29	0	0	0	0	0	13.43	1.61	25
37	19	0	0	0	1	1.4	0	0	0	0.1	0	2.5	7.35	16	0	0	0	0	0	9.72	1.19	15
38	29	0	0	0	0	0.1	0.2	0	0	0	0	0.2	18.92	31	0	0	0.007	0.007	0.02	17.90	1.61	31
39	36	2.4	0	0	0	0.4	0	0.7	0	0	0	3.5	10.08	26	0	0	0	0	0	9.70	1.38	19
40	30	1	0.4	0	0	0.5	0	0	0	0	0	1.9	14.23	25	0	0	0.003	0.003	0.01	17.71	1.05	23
41	16	0	0	0	0	0	0	0	0	0	0	0.0	10.28	14	0	0	0	0	0	7.11	1.15	17
42	22	0	0	0	0	0	0	0	0	0	0	0.0	10.17	11	0	0	0	0	0	7.36	1.20	10
43	1	0	0	0.1	0	0.3	0.5	0	0	0.1	0	1.0	0.00	4	0	0	0	0	0	2.13	0.22	3
44	28	1	0	0	0	0.6	0	0	0	0	0	1.6	12.09	21	0	0	0	0	0	13.34	1.45	26
45	21	0	0	0	0	0	0	0	0	0	0	0.0	12.39	14	0	0	0	0	0	10.62	1.28	15
46	25	0	0	0	0	0.6	0	0	1.8	0	0	2.4	15.02	18	0	0	0	0	0	8.69	1.31	16
47	21	0	0	0	0	0.1	0	0	0	0	0	0.1	14.52	6	0	0	0	0	0	11.04	1.45	9
48	19	0	0	0	0	1.2	0	0	4	0	0	5.2	11.62	28	0	0	0	0	0	11.30	1.49	19
49	26	0	0	0	0	0.1	0	0	0	0	0	0.1	14.29	27	0	0	0	0	0	9.24	1.35	20
50	16	0	0	0	0.1	0.4	0	0.8	0	0	0	1.3	15.54	13	0	0	0	0	0	11.70	1.50	12
51	30	2.9	0.7	0	0	1.3	0	0.9	0	1.1	0	6.9	12.56	24	0	0.774	0.1	0.874	0.28	20.11	1.28	22
52	6	0	0	0	0	0.4	0.4	0	0	0	0	0.8	0.93	6	0	0	0	0	0	2.37	0.35	8

Table B.4 – *Continued*

53	27	0.9	0	1.2	0	0.8	0	0	0	0	0	2.8	15.65	22	0.096	0	0	0.096	0.04	20.94	0.48	20
54	40	2.6	0.2	0	0	0.3	0	0.1	0	0	0	3.1	11.87	29	0	0	0	0	0	10.28	1.42	23
55	26	1.9	0	0	0	2	0.2	0.4	0	0.2	0.0	4.7	10.20	21	0	0	0	0	0	14.88	1.36	18
56	27	0	0	0	0	0	0	0	0	0	0	0.0	0.00	2	0	0	0	0	0	7.13	0.96	13
57	23	0.3	0	0	0	0	0.2	1.5	0	0.3	0.2	2.6	5.43	8	0	0	0	0	0	4.84	0.84	9
58	20	0	0	0	0	0	0	0	0	0	0	0.0	10.76	17	0	0	0	0	0	10.23	1.29	16
59	26	0	0	0	0	0	0	0	0	0	0	0.0	9.36	30	0	0	0	0	0	10.86	1.31	15
60	12	0.7	0	1.1	0	0	0.9	1	0.5	0.1	0.1	4.3	14.61	16	0	0	0	0	0	6.59	0.53	9
61	16	0	0	0	0.7	0.5	0	0	0	0.5	0.4	2.1	9.77	16	0	0.006	0	0.006	0.02	13.78	1.26	15
62	3	0	0	0	0	0.3	0.5	0	0	0	0	0.8	0.00	2	0	0	0	0	0	1.44	0.28	3
63	34	1.9	0	0	0	0.6	0	0	0	0	0	2.5	13.31	33	0	0	0	0	0	13.16	1.37	24
64	42	2.1	0	0	0	0.1	0	0.1	0	0	0	2.3	12.79	39	0	0	0.004	0.004	0.02	12.21	1.53	36
65	27	1.3	0	0	0	1	0	0.8	0	0	0	3.2	11.94	23	0	0	0	0	0	14.99	1.18	23
66	27	0.5	0	0	0.5	0.6	0	0	1.7	0	0	3.3	18.25	16	0	0	0	0	0	12.58	1.57	21
67	33	2.1	0	0	0	0.5	0	0.2	1	0	0	3.8	15.60	20	0	0	0	0	0	15.89	1.71	18
68	30	1	0	0	0.1	0.4	0	0	0	0	0	1.5	17.12	19	0	0	0	0	0	12.65	1.58	14
69	18	0	0	0	0	0	0	0	0	0	0	0.0	10.29	20	0	0	0	0	0	6.38	1.11	26
70	29	1	0	0.8	0.3	0.5	0	0	0	0	0	2.5	17.38	27	0	0	0	0	0	15.71	1.40	23
71	18	0	0	0	0	0.8	0	1.3	0	0	0.0	2.1	5.30	15	0	0	0	0	0	6.10	1.03	15
72	21	0	0	0	0	0	0	0	0	0	0	0.0	11.64	11	0	0	0	0	0	8.26	1.26	5
73	22	0	0	0	0	0	0	0	0	0	0	0.0	13.26	19	0	0	0	0	0	10.63	1.17	9
74	25	0	0	0	0	0.3	0	0.6	0	0	0	1.0	6.66	20	0	0	0	0	0	6.54	1.12	19
75	17	0	0	0	0	0	0.2	0	0.2	0	0	0.3	3.35	17	0	0	0	0	0	2.79	0.66	20
76	36	1.9	0	0	0	0.3	0	0	0	0	0	2.2	12.23	16	0	0	0	0	0	12.71	1.56	8
77	28	1.8	0	1.9	0	1	0	0.8	0	0.1	0	5.6	13.06	28	0	0	0	0	0	16.58	1.31	28
78	5	0	0	0	0	0.3	0.4	0	0	0	0	0.7	0.00	3	0	0	0	0	0	0.80	0.28	2
79	46	1.6	0	0	0	0	0	0	0	0	0	1.6	13.12	18	0	0	0.222	0.222	0.18	15.65	1.29	16
80	12	0.6	0.2	0	0	0.1	0.8	0	0.6	0	0	2.3	10.09	18	0	0	0	0	0	4.73	0.44	5

Table B.4 – *Continued*

81	24	0	0	0	0	1.5	0	0.1	1.7	0	0	3.4	10.41	18	0	0	0	0	0	15.39	1.50	21
82	24	0	0	0	0	0	0	0	0	0	0	0.0	10.62	21	0	0	0	0	0	10.03	1.37	34
83	6	0	0	0	0	0	1.2	0	0	0.2	0.1	1.6	1.33	2	0	0	0	0	0	1.44	0.18	2
84	43	1.4	0	0	0	0	0	0	0	0	0	1.4	13.48	19	0	0	0.002	0.002	0.01	12.13	1.49	18
85	27	0	0	0	0	0	0	0	0	0	0	0.0	11.35	16	0	0	0	0	0	8.48	1.29	19
86	22	0	0.2	0.1	0	0.1	0.8	0	0.7	0	0	2.0	10.19	18	0	0	0	0	0	6.64	0.46	15
87	15	0	0	0	0	0.2	0	0	0	0	0	0.2	14.58	0	0	0.023	0	0.023	0.06	13.68	1.57	8
88	33	1.6	0	0	0	0.4	0	0	0	0	0	2.0	12.87	25	0	0	0	0	0	13.91	1.57	34
89	15	0.1	0	0	0	0	0.1	0	0	0	0	0.2	6.51	14	0	0	0	0	0	4.75	0.90	13

Table B.5 The Notations of Selected Treatments in BDI Model

u in the 1st stage											
u1	u2	u3	u4	u5	u6	u7	u8	u9	u10	u11	u12
$RxGr6_1$	$RxGr3_1$	$ProcGr9_1$	$RxGr8_1$	$RxGr5_1$	$ProcGr10_1$	$RxGr1_1$	$RxGr2_1$	$RxGr4_1$	$ProcGr1_1$	$RxGr7_1$	$ProcGr4_1$
u in the 2nd stage											
u1	u2	u3	u4								
$RxGr3_2$	$ProcGr4_2$	$RxGr5_2$	$RxGr4_2$								

Table B.6 SDP Re-optimization Result of PDA model

	Pre	u in the 1st stage (from SDP re-optimization)												MidPDA			u in the 2nd stage				PostPDA				
	PDA	1	2	3	4	5	6	7	8	9	10	11	12	TU	SDP	Orig.	1	2	3	4	TU	StD	SDP	StD	(Orig.)
1	10	1.8	0	0	0	0	0.1	0	0.8	0	0	0	0	2.7	1.27	7	0	0	4.3	0	4.3	0.74	1.24	0.76	8
2	10	0.9	0	0	0	0	0	0	0.2	0	0.3	0	0	1.4	0.43	8	0	0	4.2	0.4	4.6	0.61	0.39	0.33	8
3	7	0	0	0	0	0	0	0	0	0.1	0.2	0	0	0.3	1.45	5	0	0	0.6	1.3	1.8	1.00	1.64	0.44	3
4	9	0	0.9	0	0	0	0	0	0.5	0	0.6	0	0	2	2.81	4	0	0.1	3.8	1.7	5.7	1.32	2.33	0.77	2
5	8	0	0.2	0	0	0	0	0	0.6	0	0.3	0	0	1.1	1.48	8	0	0	3.3	1.3	4.6	1.15	1.65	0.66	8

Table B.6 – *Continued*

6	8	0.5	0	0	0	0	0.2	0	1.3	0	1.7	0	0	3.7	1.21	5	0	0	4.8	2.3	7.1	0.80	3.22	0.79	1
7	2	0	0	0.2	0.9	3.9	0.2	0	0.5	0.3	0.4	0	0	6.4	1.61	4	0	0	4.5	1.3	5.8	0.79	1.68	0.74	3
8	9	1.8	0	0	0	0	0	0.1	0.9	0	0	0	0	2.8	1.46	9	0	0	4.5	0.7	5.2	0.73	0.79	0.53	8
9	7	0	0	0	0	0	0	0	0.3	0.1	0.5	0	0	0.9	2.01	6	0	0	1.6	1.1	2.7	1.18	1.36	0.45	5
10	9	0.5	0	0	0	0	0	0	0	0	0	0	0	0.5	1.43	6	0	0	0	0.9	0.9	0.43	1.10	0.52	5
11	7	0	0	0	0	0	0	0	0	0	0.1	0	0	0.1	0.21	8	1.1	0	3.2	1.1	5.4	0.98	1.44	0.54	7
12	9	0.3	0	0	0	0	0	0	0.7	0	0.6	0	0	1.5	0.48	8	0	0	4.7	1.5	6.2	0.86	1.97	0.67	8
13	8	0	0	0	0	0	0	0	0.8	0	0	0	0	0.8	2.31	6	0	0.1	4.2	0	4.3	1.39	2.46	1.01	6
14	7	0	0	0	0	4.2	0	0.2	0	0	1	0	0	5.3	1.04	4	0	0	0.6	1.1	1.6	0.92	1.37	0.31	3
15	9	0	0	0	0	0	0	0	0.2	0.1	0	0	0	0.4	1.28	5	0	0	4	0.6	4.6	0.70	0.65	0.45	6
16	9	0.8	0	0	0	0	0	0	0.8	0	0.2	0	0	1.8	0.91	7	0	0	3.9	0.3	4.3	0.60	0.32	0.30	5
17	6	0	1.9	0	0	0.7	0.7	1.5	1.9	0	0	0	0	6.7	3.30	5	0	1.4	2.4	2.6	6.4	1.85	3.57	0.59	4
18	8	0.6	0	0	0	0	0	0	1.3	0.3	0.9	0	0	3.1	2.41	7	0	0.1	4.4	1.7	6.1	1.02	2.20	0.79	7
19	7	1.7	0	0	0	0	0.1	0	0.4	0.4	1.3	0	0	3.9	1.22	5	0	0	5	2.1	7.2	0.58	2.89	0.77	4
20	7	0	0	0	0	0.2	0	0	0.3	0	0.1	0	0	0.6	0.95	3	0	0	0.8	0.7	1.6	0.97	0.91	0.40	6
21	10	1.2	0	0	0	0	0	0	1.3	0.7	0	0	0	3.1	1.74	3	0	0	2.4	0	2.4	1.09	1.11	0.60	3
22	7	1.3	0	0	0	0	0	0	1.5	1.7	0	0	0	4.6	0.41	4	0	0	4.5	1.2	5.7	0.78	1.52	0.73	4
23	2	0	0	0.1	0	0	0	0	0.3	0	0.5	0	0	1	0.66	2	0	0	0.1	1.9	2	0.57	2.51	0.35	0
24	7	0	0	0	0	2.5	0	0	0.3	0	0.5	0	0	3.3	0.60	6	0	0	0.1	0.6	0.6	0.32	0.67	0.22	4
25	7	0	0	0	0	0	0	0	1	0.1	0	0	0	1.1	2.48	2	0	0	1	1.8	2.8	1.38	2.37	0.53	2
26	9	1.4	0	0	0	0	0	0.9	1.2	0	0	0	0	3.6	1.92	8	0	0	3.6	1.7	5.3	1.38	2.29	0.79	7
27	8	0.5	0	0	0	0	0	0	0.8	0.9	0.3	0	0	2.4	1.43	6	0	0	4.2	1.3	5.6	0.97	1.75	0.76	1
28	6	0	0.4	0	0	0.3	0	0	0	0	0.1	0	0	0.9	0.95	2	0	0	0	0.7	0.7	0.30	0.80	0.43	4
29	9	0	0	0	0	0	0	0	0.1	0	0.2	0	0	0.3	0.30	5	0	0	1.6	0.6	2.2	0.87	0.71	0.34	5
30	8	0	0	0	0	0	0.4	0	1.6	1.5	0	0.3	0	3.8	1.94	4	1.1	0	3.8	0	5	1.04	1.55	0.72	4
31	3	0	0	0.1	0	0	0	0	0.7	0	0.4	0	0	1.2	1.62	3	0	0	0.1	1.3	1.4	0.49	1.73	0.35	5
32	5	0	0	0	0	0	0	0	0.3	0	0.5	0	0	0.8	0.61	5	0	0	1	0	1	1.14	1.47	0.49	1
33	6	0	0.8	0	0	0	0	0.3	0.9	0	0.8	0	0	2.8	1.99	7	0	0	0	1.3	1.3	1.01	1.69	0.71	8

Table B.6 – *Continued*

34	8	0	0	0	0	0	0	0	0.2	0	0.3	0	0	0.5	0.40	3	0	0	3.4	0.7	4.2	0.66	0.89	0.49	3
35	5	0.6	0	0.1	0	0	0.7	0	2.3	0	0	0	0	3.8	3.25	3	0	0	0.2	0	0.2	0.76	4.35	0.62	4
36	6	0	0	0	0	0	0	0	0.3	0	0.4	0	0	0.7	1.03	10	0	0	2.5	1.7	4.2	1.52	2.22	0.63	8
37	5	0	0	0	0	0	0	0	0.8	0.1	0.3	0	0	1.2	1.80	7	0	0	0.9	1.5	2.4	1.23	2.03	0.45	5
38	8	0	0	0	0	0	0	0	0.5	0	0.2	0	0	0.7	1.13	7	0	0	1.6	1.6	3.2	1.46	2.08	0.53	7
39	9	1.5	0	0	0	0	0	0.1	0	0	0	0	0	1.6	0.25	4	0	0	4.1	0	4.1	0.62	0.68	0.45	3
40	7	0.8	0	0	0	0	0.2	0	0	0.5	0	0	0	1.5	2.27	7	0	0	0	1	1	0.36	1.21	0.50	3
41	5	0	0	0	0	0	0.3	0	1.2	0	1.7	0	0	3.2	1.86	5	0	0	3.6	3	6.6	2.01	5.96	0.85	3
42	8	0	0	0	0	0	0	0	0.2	0	0.2	0	0	0.4	0.37	2	0	0	3.4	0.8	4.1	0.72	0.94	0.51	5
43	4	0	0	0	0	0.6	0	0	0.1	0	0.3	0	0	1	0.33	3	0	0	0.2	0	0.2	0.60	1.71	0.28	3
44	8	0.3	0	0	0	0	0	0	0	0	0.3	0	0	0.6	0.51	2	0	0	0	1	1	0.36	1.21	0.44	4
45	5	0	0	0	0	0	0	0	0.3	0	0	0	0	0.3	1.43	2	0	0	0.9	1.5	2.4	1.25	1.95	0.49	2
46	8	0	0	0	0	0	0	0	0.2	0.1	0.1	0	0	0.4	1.56	3	0	0	4.2	1.2	5.4	0.92	1.53	0.73	6
47	7	0	0	0	0	0	0	0	0.6	0.1	0.1	0	0	0.7	1.46	0	0	0	0	1.1	1.1	1.17	1.35	0.53	0
48	6	0	0	0	0	0	0	0	0.3	0	0.5	0	0	0.8	0.60	4	0	0	1.6	1.3	2.9	1.34	1.77	0.46	7
49	10	0	0	0	0	0	0	0	0.2	0	0.2	0	0	0.4	0.59	7	0	0	4.9	1.1	6	0.60	1.47	0.74	6
50	3	0	0	0	0	0	0	0	0.6	0	0	0	0	0.7	1.64	5	0	0	2	1.4	3.4	1.40	1.83	0.58	2
51	8	0.9	0	0	0	0	0	0.3	1	0.3	0.3	0	0	2.7	2.20	8	0	0.1	4.6	1.1	5.7	0.75	1.36	0.70	5
52	5	0	0	0	0	0.6	0	0	0.4	0	0.3	0	0	1.3	0.98	3	0	0	0.2	0.8	1	0.56	0.96	0.33	2
53	4	1.4	0	0.2	0	0	0.3	0	0	0	0	0	0	2	1.95	4	0	0	0	1.1	1.1	0.33	1.35	0.47	2
54	8	1.9	0	0	0	0	0	0	0	0	0	0	0	1.9	0.02	6	0	0	0	0.4	0.4	0.56	0.48	0.36	8
55	7	0.1	0.1	0	0	0	0	0	1.5	0.8	0	0	0	2.5	3.25	5	0	0	0	2.2	2.2	1.77	2.99	0.73	3
56	7	0	0	0	0	0	0	0	0	0	0.1	0	0	0.1	0.21	1	0	0	0.2	0.2	0.3	0.44	0.05	0.23	2
57	8	0	0.3	0	0	0	0.4	0	1.1	0	0.1	0	0	1.9	2.22	1	0	0	2.1	0.5	2.6	0.84	0.57	0.39	2
58	7	0	0.1	0	0	0.3	0	0	1.1	0	0.7	0	0	2.1	2.39	6	0	0	1.7	1.9	3.5	1.59	2.54	0.54	4
59	7	0.2	0	0	0	0	0	0	0.6	0.1	0	0	0	0.8	2.15	7	0	0	1.3	1.8	3.1	1.47	2.36	0.55	7
60	8	0	1.8	0	0	3	0	0	1.4	0	1.8	0	0	7.9	2.28	4	0	0	3.6	1.5	5.1	1.20	1.95	0.70	4
61	6	0	0	0	0	0	0.2	0.7	0	0.7	0	0	0	1.6	2.30	4	0	0	0	0.8	0.8	0.36	0.93	0.51	3

Table B.6 – *Continued*

62	6	0	0	0	0	0.7	0	0	0.2	0	0	0	0	0.9	1.32	5	0	0	0.4	0.8	1.2	0.76	1.01	0.34	2
63	7	2	0	0	0	0	0.2	0	0.4	0.9	0	0	0	3.4	1.35	7	0	0	1.7	1.1	2.8	1.21	1.35	0.51	2
64	10	1.3	0	0	0	0	0	0	0.5	0.7	0	0	0	2.5	0.68	10	0	0	4.3	0.6	4.9	0.67	0.73	0.49	7
65	8	1.9	0	0	0	0	0.1	0	0	0	0	0	0	2	1.12	7	0	0	0	0	0	0.12	2.37	0.63	6
66	6	0.7	1.8	0	0	0	0	0	1.7	0	2.2	0	0	6.4	2.26	7	0	1.4	4.4	2.6	8.3	1.27	3.55	0.65	6
67	9	1	0.4	0	0	0	0	0	0.8	0.1	0.8	0	0	3.1	1.95	8	0	0	0	1.8	1.8	1.30	2.34	0.77	7
68	8	1.2	1.4	0	0	0	0	0	0.9	0	1.4	0	0	4.9	1.53	7	0	0	0	1.1	1.2	0.59	1.44	0.71	4
69	8	0	0	0	0	0	0	0	0.1	0	0.2	0	0	0.2	0.29	4	0	0	2	0.6	2.6	0.80	0.67	0.36	5
70	7	0.3	0	0	0	0	0	0	1	0.9	1.5	0	0	3.7	1.68	7	0	0.1	1.8	2.9	4.8	1.97	4.12	0.54	7
71	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0.06	5	0	0	0.1	0.7	0.8	0.43	0.84	0.41	5
72	8	0	0.2	0	0	0	0	0	0.5	0.1	0	0	0	0.8	1.34	2	0	0	2.5	0.9	3.4	1.04	1.11	0.52	2
73	6	0	0	0	0	0	0	0	0.1	0.2	0.3	0	0	0.6	0.70	3	0	0	0.5	1.1	1.6	0.90	1.48	0.40	5
74	9	0	0.1	0	0	1.2	0.3	0	1.2	0	1.2	0	0	3.9	2.25	6	0	0	3.6	2.7	6.3	1.70	3.87	0.77	4
75	10	0	0	0	0	0	0	0	0.5	0.2	0.2	0	0	0.8	0.84	7	0	0	2.4	0.9	3.3	0.97	1.09	0.48	8
76	7	1.8	0	0	0	0.1	0	0	0	0.1	0.2	0	0	2.2	0.81	6	0	0	0	1.3	1.3	1.09	1.70	0.70	4
77	8	0.2	0.3	0	0	0	0	0	1.1	0.5	0	0	0	2.1	2.57	5	0	0.1	3.5	1.9	5.4	1.50	2.51	0.79	8
78	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00	1	0	0	3.5	0.8	4.2	0.52	0.97	0.49	2
79	8	0.7	0	0	0	0	0	0	0.6	0.5	0	0	0	1.9	2.20	6	0	0	2.2	1.8	4	1.62	2.40	0.65	4
80	7	0	0	0	0	0	0	0	0.4	0	0.6	0	0	1	0.71	6	0	0	0.7	1.2	1.9	1.02	1.61	0.36	6
81	7	0.1	0	0	0	0	0	0	0.8	0	1	0	0	1.9	1.13	3	2.3	0	0.3	2.4	5.1	0.94	3.32	0.30	7
82	8	0	0	0	0	0	0	0	0.1	0	0	0	0	0.2	1.22	9	0	0	2.2	1.5	3.8	1.46	2.03	0.61	8
83	6	0	0	0	0	1.9	0	0	0.7	0	1.1	0	0	3.6	1.14	2	0	0	1.7	1.3	3	1.31	1.72	0.45	3
84	7	0.8	0	0	0	0	0	0	0.6	0.2	0.2	0	0	1.9	1.62	6	0	0	2.6	1.5	4.1	1.42	1.99	0.65	6
85	9	0	0	0	0	0	0	0	0.2	0	0.1	0	0	0.3	0.61	7	0	0	3.1	1	4.1	0.95	1.23	0.57	8
86	9	0.3	0.2	0	0	0	0.2	0	0	1.3	0	0	0	2	1.49	7	0	0	0	0.4	0.4	0.30	0.35	0.49	3
87	6	0	0	0	0	0	0	0.1	1.6	0	0	0	0	1.7	2.61	2	0	0	4.8	1.5	6.3	0.69	1.95	0.83	2
88	6	1.3	0.1	0	0	0	0	0	1	0.4	0.3	0	0	3.2	2.25	6	0	0	0	1.8	1.8	1.50	2.40	0.74	5
89	8	0	0.6	0	0	0.8	0	0	1	0	0.7	0	0	3.1	2.03	7	0	0	2.5	1.8	4.3	1.60	2.44	0.64	6

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