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THE INFLUENCE OF PROJECTION BIAS ON OUTCOMES OF HEALTHCARE
FINANCIAL INCENTIVE PROGRAMS

by

Jordyn Bader

A THESIS

Presented to the Faculty of
The Graduate College at the University of Nebraska
In Partial Fulfillment of Requirements
For the Degree of Master of Science

Major: Agricultural Economics

Under the Supervision of
Professor Christopher Gustafson

Lincoln, Nebraska

August, 2016

THE INFLUENCE OF PROJECTION BIAS ON OUTCOMES OF HEALTHCARE FINANCIAL INCENTIVE PROGRAMS

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University of Nebraska, 2016

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This thesis contributes to the behavioral health literature and literature regarding healthcare financial incentive programs by discussing the influences of the behavioral economic concept of projection bias on programs designed to recruit healthcare providers to rural or underserved areas. First, I propose an adaptation to the model of projection bias by introducing a term that captures variability in individuals' propensity to exhibit projection bias based on the amount of effort expended in predicting future preferences. Next, I conduct a probit model regression to observe what incentive program design features and participant characteristics are likely to influence the probability of exhibiting projection bias and therefore affect the efficacy of two incentive programs. Results suggest that incentive programs targeted to students are more likely to experience higher magnitudes of projection bias among participants, resulting in higher default rates, compared to professional-targeted programs. This is potentially due to the temporal gap, or length of time between when an individual decides to participate in the incentive program, thereby agreeing to practice in a shortage area in the future, and carrying out the service obligation. Furthermore, within the student-targeted program, the longer the training of participants, the more prone they are to exhibit projection bias and default on their obligation. This research also includes a survival analysis to identify what variables are related to a longer length of practice in one's initial shortage area.

ACKNOWLEDGEMENTS

I want to thank the many individuals who assisted me throughout this experience. First, thank you to my advisor and committee chair, Dr. Christopher Gustafson, who provided guidance and affirmation throughout the research process. You have inspired my curiosity for behavioral economics and have taught me a great deal throughout our time working together. I am also grateful for my committee members, Dr. Taro Mieno and Dr. Connie Reimers-Hild. I appreciate the support and positivity from Dr. Mieno who provided assistance and direction throughout the analysis process and from Dr. Connie Reimers-Hild for her incredible mentorship regarding graduate school and beyond. Thank you all for investing in me. I appreciate the partners from the Nebraska Department of Health and Human Services, Thomas Rauner and Marlene Janssen, who answered many questions, provided data, and lent their expertise about healthcare financial incentive programs. A special thank you to my husband, John, for his steadfast love and encouragement throughout this process. Finally, thank you to the administration, faculty, staff, and students in the Agricultural Economics department and at the University of Nebraska Extension and the Rural Futures Institute who have shared in and shaped my experience.

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DEFINITION OF ABBREVIATIONS

AIV	Adjusted Incentive Value
DC1	Default Condition One
DC2	Default Condition Two
DC3	Default Condition Three
HPSA	Health Professional Service Area
HPTS	Health Professions Tracking Service
LOT	Length of Training
LRP	Loan Repayment Program
OMB	Office of Management and Budget
SLP	Student Loan Program
TP1	Time Period One
TP2	Time Period Two
TP3	Time Period Three

CHAPTER 1: INTRODUCTION

1.1 Motivation

Residents of nonmetropolitan areas, which are defined as communities with populations under 50,000 residents, are one of the largest medically underserved populations in the United States. Twenty percent of the U.S. population lives in nonmetropolitan areas, yet less than ten percent of primary care providers practice in such areas (Rosenblatt and Hart 2000). In addition to a geographic imbalance of healthcare practitioners, nonmetropolitan residents suffer from higher rates of chronic diseases and disability, report higher levels of obesity, are older on average, and are more likely to report being in poorer health than their metropolitan counterparts (Ricketts 2000 and USDA ERS 2009).

In response to this healthcare disparity, federal and state programs have been established to incentivize healthcare providers to practice in geographic regions that have been identified as having a shortage of primary care, dental, and mental healthcare providers. Over 60 million Americans live in a shortage area for primary care, nearly 50 million live in a shortage area for dental care and nearly 100 million live in a shortage area for mental health (U.S. DHHS 2016). At the federal level, these shortage areas are called Health Professional Shortage Areas (HPSAs) and can be geographic areas, population groups, or facilities in which the number of healthcare providers falls beneath a designated target. Nationally, over half of HPSA designations are in nonmetropolitan counties, while in Nebraska, over 85 percent of the designations are in nonmetropolitan

counties (U.S. DHHS 2016)¹. Additionally, the State of Nebraska designates counties as state-designated shortage areas to further identify healthcare provider needs within the state.

Being designated a shortage area makes these areas eligible to benefit from programs that incentivize providers to practice there. In Nebraska, two incentive programs are administered from state funds, 1) the Nebraska Student Loan Program (SLP), and 2) the Nebraska Loan Repayment Program (LRP). Although both programs exist to help alleviate the healthcare disparity found in nonmetropolitan areas, the programs have important differences in the structure and timing of healthcare providers' decision to commit to serve in a state-designated shortage area in return for the incentive.

Under the SLP, the state awards forgivable student loans to medical, physician assistant, dental, and graduate-level mental health students who agree to practice one year in a state-designated shortage area for every year they accept the forgivable loan. This incentive is received while participants are in professional school. Under the LRP, licensed physicians, physician assistants, nurse practitioners, dentists, pharmacists, occupational and physical therapists, and mental healthcare providers receive funds to pay back student loans over the course of three years once they begin to practice in a state-designated shortage area. Both programs require that participants practice in a state-designated shortage area for a certain period of time in exchange for the financial incentive (NE DHHS 2015a). Both the SLP and LRP have experienced financial and administrative changes over time. These changes include increased monetary incentives, changes to the cost of defaulting—that is, not completing one's practice obligation in a

¹Healthcare facilities in metropolitan areas may also be designated a Health Professional Shortage Area and may be eligible to receive state and federal funds.

shortage area—as well as sending service obligation reminders to participants of the SLP. Table 1.1 summarizes the differences between the programs and changes in the programs over time.

Previous studies have found differences in outcomes between student-targeted and professional-targeted incentive programs. In this particular study, since its inception in 1979, nearly 45 percent of SLP participants have failed to complete their practice obligation, compared to only eight percent of LRP participants. This difference in completion rate, given the structural differences of the programs, may be partially explained by a behavioral economic concept known as *projection bias*. Projection bias refers to an individual's tendency to exaggerate the degree to which their future preferences reflect their current preferences (Loewenstein, O'Donoghue, and Rabin 2003). In these incentive programs, the differences in timing of the decision to participate in a program may lead to a higher probability of projection bias in the SLP compared to the LRP. In the SLP, individuals commit to practicing in a state-designated shortage area while attending school in exchange for a forgivable student loan. In this program, an individual must predict their future preferences years in advance (up to seven years in the case of a medical student), compared to LRP participants, who receive the incentive once they are practicing and make their decision to participate a year or two before they begin practice in a shortage area.

Other program design features may also contribute to the likelihood of individuals exhibiting projection bias. For example, changes to the cost of default may influence the perception of how costly or binding their decision to participate is. If the cost of defaulting changes, it is possible that individuals will spend more time considering their

true future practice preferences in order to make more accurate predictions, decreasing the likelihood of defaulting on their obligation. Furthermore, participant characteristics such as their background and previous experiences – e.g., whether that person has lived in a nonmetropolitan area before or not – may also affect his or her ability to accurately predict future preferences (Kahneman and Thaler 2006).

Projection bias provides a theoretical explanation for the observed differences in default rate between the SLP and LRP, and the existence of projection bias would make a program that requires individuals to commit to practicing in a shortage area years in advance inherently less successful than one that has a shorter time lag between committing to a shortage area and carrying out the decision. These differences in completion rate suggest that design features of incentive programs should be carefully considered in light of projection bias. By understanding what program and personal characteristics exacerbate or counteract the magnitude of projection bias, thereby affecting the outcomes of financial incentive programs, similar state and federal healthcare incentive programs can adapt policies and processes to positively influence the success rate of recruiting healthcare providers to serve high need populations.

1.2 Objectives

The first objective of this research is to apply a model of projection bias to healthcare incentive programs. First, this research proposes an adaptation to the model of projection bias by introducing a term that captures variability in individuals' propensity to exhibit projection bias based on the amount of effort an individual expends in predicting their future preferences. This modification suggests that the perception of how binding a decision is influences the magnitude of projection bias. Next, this project

examines how program design features such as the timing of when an incentive is received or the cost of default influence one's likelihood of exhibiting projection bias, thereby effecting program outcomes. This objective addresses the influence of projection bias on the efficacy of incentive programs created to recruit healthcare providers into state-designated shortage areas.

The second objective of this research is to examine the implications of projection bias and program design on the length of service in one's initial practice location. Specifically, this research will observe the length of practice among participants' initial shortage area practice locations and discuss which individual and program design variables are most predictive of longer retention of healthcare providers.

1.3. Contribution to the Literature

This research contributes to literature in the behavioral economics and rural health fields. First, this thesis extends the theory of projection bias by introducing a variable expected to influence the magnitude of bias exhibited by individuals. Additionally, it proposes that program design can induce or reduce the occurrence of projection bias, demonstrating that structural features of programs may influence the quality of decisions individuals make. While the effectiveness of healthcare financial incentive programs has been well researched, this analysis applies behavioral economic principles to describe why similar programs experience different outcomes. Looking at financial incentive programs through the lens of behavioral economics provides a new perspective and potential strategies to improve program outcomes.

1.4 Definition of Rural

Because the majority of healthcare shortage areas in Nebraska are in places that would be considered “rural,” it is important to establish a precise definition of the term that will be used throughout this thesis. Although several definitions of rural exist, the key dimension of rural is geographic dispersion of population and lesser access to markets for services and jobs (USDA ERS 2009). This research utilized the Office of Management and Budget’s (OMB) county-based metropolitan and nonmetropolitan classification because this definition is used extensively at the federal level for healthcare policy, including programs designed to increase healthcare providers in rural areas (Hart, Larson and Lischner 2005).

As of 2013, the OMB defined metropolitan (metro) counties as broad labor-market areas that include central locations with one or more urbanized core – i.e., cities with a population greater than or equal to 50,000 – and outlying counties that are economically tied to the core, as measured by labor-force commuting. Nonmetropolitan (nonmetro) counties are outside the boundaries of metro areas and are further subdivided into two types. Micropolitan (micro) areas are nonmetro labor-market areas centered on populations between 10,000-49,999 and outlying counties that are economically tied to the core. Noncore counties are all remaining nonmetro counties because they are not part of the “core-based” metro or micro areas (U.S. OMB 2013). Based on these definitions, the State of Nebraska has 13 metropolitan, 17 micropolitan, and 63 noncore counties as of 2013 (U.S. OMB 2013).

1.5 Description of Incentive Programs

The State of Nebraska's Department of Health and Human Services, Office of Rural Health designates state shortage areas every three years. These designations are based on a variety of variables including physician-to-population ratio, proportion of elderly population, proportion of population below the poverty level, health indicators such as infant mortality rate and low birth rate, and the age of existing healthcare workforce in the geographic region (NE DHHS 2015b). Descriptions of the SLP and LRP incentive programs that are funded and administered by the State of Nebraska are outlined below. A summary of this information can be found in Table 1.1.

1.5.1 Incentive Amounts and Eligible Recipients

Under the SLP, the state awards forgivable student loans to Nebraska medical, physician assistant, dental, and graduate-level mental health students who agree to practice for one year in an approved specialty, state-designated shortage area for every year they accept the incentive. The nominal incentive amount has changed over time. This program started in 1979 by awarding low-interest loans to medical students. In 1991, the program switched from providing low-interest loans to forgivable student loans to Nebraska medical and physician assistant students in the amount of \$10,000 and \$5,000 per year, respectively. In 1998, the nominal incentive value increased and more professions became eligible. The SLP awarded forgivable student loans in the amount of \$20,000 to Nebraska medical and dental students, and \$10,000 to physician assistant and master's level mental health students (NE DHHS 2015a).

The LRP is available to physicians, nurse practitioners, and physician assistants practicing in primary care specialties – e.g., family practice, general internal medicine,

general pediatrics, obstetrics/gynecology, general surgery, and psychiatry – dentists, clinical psychologists, licensed mental health practitioners, pharmacists, occupational therapists, and physical therapists. Under the LRP, participating healthcare providers receive funds, provided from a 50-50 state and local match, to pay back student loans for three years once they begin to practice in a state-designated shortage area. Beginning in 1994, primary care physicians, dentists, and psychologists received up to \$20,000 per year for three years, and nurse practitioners, physician assistants, and master's level mental health professionals received up to a \$10,000 per year for three years. Dentists, pharmacists, and occupational and physical therapists were added to program eligibility in 1998. In 2006, the per-year incentive increased to \$40,000 and \$20,000, respectively. These funds require the recipient to complete a three-year practice obligation in a state-designated shortage area (NE DHHS 2015a).

1.5.2 Timing of Incentive Received

One important distinction between these two programs is the timing of the delivery of the incentive. In the SLP, individuals receive the incentive while in professional school, and by participating, agree to practice in a state-designated shortage area years before they are licensed to practice. LRP participants receive the incentive once they are licensed and a practicing professional. LRP participants choose to participate in the program towards the end of their training and typically make the decision to participate in this program a year or two before beginning practice in shortage area.

1.5.3 Default Cost and Administrative Changes

Failure to practice in a state-designated shortage area for the time required of these incentive programs results in a default outcome. Default may occur prior to practicing in a shortage area, in the case of the SLP, or it may occur after beginning practice in a shortage area if an individual moves practice locations prior to completing the time required of the obligation.

Failure to complete a practice obligation comes at a financial cost to the program participant. While the cost of default under the LRP has remained constant over time for the sample in the study – 125 percent of funds received – the SLP has implemented administrative and default cost changes over time. Prior to 1998, in default condition one (DC1), the cost of default was 24 percent simple interest from the date the incentive was received. Administrative changes were made in 1998, which marks the beginning of default condition two (DC2). At this time, SLP participants began receiving semi-annual letters reminding them of their practice obligation to the State of Nebraska and the cost to the individuals if they defaulted on their obligation. Participants received these letters twice a year until their obligation was completed. The default cost remained at 24 percent simple interest from the date the incentive was received. In 2007, the beginning of default condition three (DC3), the default cost changed to 150 percent principal plus 8 percent simple interest from the date of default. The semi-annual letters continued in this condition (NE DHHS 2015a).

1.6 Organization of Work

Chapter 2 provides a review of the literature regarding the efficacy of healthcare financial incentive programs at recruiting and retaining healthcare providers in shortage

areas. Additionally, this chapter discusses the influence of projection bias on economic and medical decisions and what may cause projection bias among financial incentive programs. Chapter 3 provides a theoretical framework of projection bias as it relates to healthcare financial incentive programs and proposes a modification to the model of simple projection bias. This chapter also derives hypotheses of variables expected to be influenced by projection bias. Chapter 4 discusses the sample used in this research and provides summary statistics of the data. The empirical models – i.e., probit model and survival analysis models including a Kaplan-Meier survival probability and cox proportional hazards regression – used to test hypotheses are discussed in Chapter 5. Chapter 6 provides results and discussion of the analysis, and a summary of this research is discussed in Chapter 7.

Table 1.1

Nebraska Rural Health Incentive Program Descriptions

	Student Loan (SLP)	Loan Repayment (LRP)
Timing of Incentive	Received as student	Received as licensed professional
Practice Obligation	One year service per year incentive received	3-years
Eligible Professions	Medical, dental, physician assistant, and graduate-level mental health students	Physicians, nurse practitioners, and physician assistants in primary care specialties; dentists, psychologists, licensed mental health practitioners, pharmacists, occupational therapists, and physical therapists
Incentive Amount 1: 1979-1990 2: 1991-1997 3: 1998-2015 4: 1994-2005 5: 2006-2015	<u>Varies by Period:</u> 1: Low-interest loan 2: Forgivable Loan (10K, 5K) 3: Forgivable Loan (20K, 10K)	<u>Varies by Period</u> 4: 20K, 10K (per year) 5: 40K, 20K (per year) (50-50 state & local match)
Default Cost & Administrative Oversight² 1: 1979-1997 2: 1998-2006 3: 2007-2015 4: 1994-2015	<u>Varies by Period</u> 1: 24% interest 2: 24% interest & semi-annual letter 3: 150% principal + 8% interest & semi-annual letter	4: 125% funds received
Overall Average Default Rate	43%	8%

² Default cost in the LRP has changed from 125% since 2015, but does not affect the sample included in the research.

CHAPTER 2: LITERATURE REVIEW

2.1 Rural Healthcare Disparities

The persistent concern about access to healthcare services among vulnerable populations, including residents of nonmetropolitan areas, has prompted innovative solutions and policy interventions to help address the issue. Some of these efforts include utilizing telehealth to extend and improve access to care for those facing geographic barriers to healthcare services, a solution particularly useful among the behavioral healthcare field (Ricketts 2000); focusing on public health, or population-based preventive approaches that address systematic factors influencing health of a population such as diabetes, mental health, or use of tobacco (Hartley 2004); training a diverse workforce of those most likely to practice among underserved populations (Jackson and Gracia 2014); exposing students to underserved populations by working in free clinics while in training (VanderWielen et al. 2015); and incentivizing healthcare providers to practice in healthcare provider shortage areas by relieving debt incurred during training.

Expanding programs or creating new interventions such as the examples above is becoming even more important as the demand for healthcare services continues to grow. Petterson et al. (2012) estimate that the U.S. will require almost 52,000 additional primary care physicians by 2025 to meet future demand. This estimate is calculated by accounting for the number of primary care office visits, U.S. Census Bureau population and demographic change projections, and the current supply of primary care providers according to the American Medical Association Masterfile (Petterson et al. 2012). Population growth is the key driver of growing demand for healthcare, followed by an aging population as well as an expected increase in demand due to expanded medical

coverage through the Affordable Care Act (Pettersen et. al 2012 and IHS Inc. 2015).

These estimates, however, do not consider the geographic distribution of healthcare providers, and the key drivers of demand will exacerbate the geographic health disparities if population growth, newly insured, or aging residents are clustered in areas already experiencing shortages of healthcare providers (Pettersen et al. 2012).

One strategy to increase the number of providers in shortage areas is to offer financial incentives. Two common incentives include student- and professional-targeted programs. Student-targeted programs involve incentives such as low-interest or forgivable educational loans or scholarships. In these programs, students commit early in their healthcare education to practice in a designated shortage area upon completion of training in exchange for the incentive. Alternatively, in professional-targeted programs, participants commit near the completion of their training to practice in a designated shortage area in exchange for assistance in repaying educational loans acquired earlier as students (Bärnighausen and Bloom 2009a).

Through these programs, participating healthcare providers enter into a legally binding contract to work for a specified number of years in a medically underserved area in exchange for a financial pay-off (Bärnighausen and Bloom 2009a). Incentive programs vary by the amount of financial incentive received, penalty for defaulting on the contract, the timing of when the incentive is received, type of commitment, and professions eligible to participate (Bärnighausen and Bloom 2009b).

Efforts like these to increase the supply of, or redistribute, healthcare providers in order to increase access and quality of care requires that policy-makers understand the economic and psychological forces at play when individuals face decisions of where to

practice. Increasing the value of practicing in an underserved area by increasing the monetary payoff for doing so by providing financial incentives may help correct for the maldistribution. However, there are additional psychological factors that are likely to influence the outcome of programs that are intended to recruit professionals to areas in need of healthcare professionals. Looking at the issue of healthcare disparities through the lens of behavioral economics could provide new insights into the way that healthcare financial incentive programs are designed and delivered.

2.2 Behavioral Economics

The field of behavioral economics seeks to improve upon theoretical frameworks of neoclassical economics by incorporating psychological foundations to make better predictions of behavior (Camerer and Loewenstein 2004). An assumption of neoclassical economics is that individuals are rational, utility-maximizing agents. However, in certain instances, individuals tend to exhibit irrational behaviors that are not accounted for in neoclassical models. For example, one's attitude towards risk is influenced by a reference point and framing, resulting in risk-aversion when facing gains and risk seeking when facing losses (Kahneman and Tversky 1979). Behavioral economics begins with rational agent models and introduces cognitive limitations of humans to more accurately explain and predict behavior. Behavioral economic insights can help explain common findings and outcomes of financial incentive programs by investigating how program design features may unintentionally induce biases—such as projection bias—that undermine the effectiveness of the program.

2.2.1 Projection Bias

To correctly make intertemporal decisions, individuals must know how their tastes will change over time. While neoclassical economic models assume individuals understand the distribution of their changes in taste, projection bias suggests that while individuals may be able to anticipate the direction of their changes in preferences—e.g., eating appetizers will diminish one's appetite for dinner or winning the lottery will improve one's quality of life—individuals systematically misestimate the magnitude of these changes (Loewenstein, O'Donoghue, and Rabin 2003). This is known as projection bias, or the tendency to exaggerate the degree to which one's future preferences reflect current preferences (Loewenstein, O'Donoghue, and Rabin 2003). For example, one may schedule an overly warm summer vacation destination if planning the vacation during the winter, or a healthy individual may overestimate the impact that being diagnosed with a chronic disease will have on their quality of life. Current preferences are dependent upon a number of factors including mood, environment, habits, or previous experiences, and empirical studies have found that individuals systematically misestimate how their tastes and preferences will change when their psychological state, mood, or environment change (Loewenstein 2000; Grable, Lytton and O'Neill 2004; Lucey and Dowling 2005).

The inability to anticipate how one's preferences will change undermines the quality of decisions that individuals make (Loewenstein 2005). Projection bias has been shown to influence behavior in a variety of domains, including the medical field (Slevin et al. 1988, Bernabei et al. 1998, Loewenstein 2005, and Halpern and Arnold 2008). A study by Slevin et al. (1988) found that individuals in a state of health inaccurately predicted what their treatment preferences would be after becoming ill. More specifically,

the researchers found that patients with cancer were much more likely to opt for radical medical treatment, even with a small chance of benefit, compared to healthy non-patients. Only 10 percent of healthy non-patients said they would accept a grueling treatment of chemotherapy to extend their life by three months, compared to 42 percent of cancer patients. Moorman and Carr (2008) studied elderly spouses' hypothetical end-of-life treatment decisions for their incapacitated spouses. Results showed that surrogate spouses— i.e., those making treatment decision that they believed their incapacitated spouses would choose— accurately predicted the incapacitated spouses' true treatment preferences between 62% and 77% of the time, demonstrating that projection bias also exists between individuals in different states.

Projection bias has also been found to influence economic decisions. A study by Grable, Lytton and O'Neill (2010) found that the previous week's closing prices, influenced by short-term price changes, changed investors' risk tolerance attitudes the subsequent week. Based on psychological evidence, Loewenstein et al. (2001) and Lucey and Dowling (2005) proposed that one's feelings or mood drives financial decisions involving uncertainty, and Lo, Repin, and Steenbarger (2005) found that trader's who exhibit intense emotional reactions to market events such as price volatility performed worse than those who had lesser emotional reactions, indicating that one's emotional state influences decisions made in that state. Loewenstein, O'Donoghue, and Rabin (2003) demonstrated how projection bias could cause individuals to consume too much early in life and too little later in life. The authors also proposed that projection bias could cause misguided purchases of durable goods. For instance, people's valuation of durable goods fluctuate daily, and projection bias would suggest that individuals will over-

purchase durable goods on high-valuation days.

2.3 Recruitment Efficacy of Incentive Programs

Current literature addresses the effectiveness of financial incentive programs in both recruiting and retaining healthcare providers in high need communities. The effectiveness of financial incentive programs varies and depends on many factors like design elements of the programs, including length of time between commitment and service, the length of service commitment, freedom in choosing practice location, as well as expectations about quality of life during the service commitment and the mission of the work involved (Miller and Crittenden 2001).

Jackson et al. (2003) found that state programs that recruit students had significantly lower recruitment success than state programs that recruit healthcare workers after their training. Pathman et al. (2004) support this finding through a study of state-funded healthcare incentive programs, reporting that student-targeted programs that obligate students to practice in shortage areas early in their training have the lowest completion rates, ranging from 44 percent to 66.5 percent. However, programs that recruit providers towards the end of their training have a completion rate of 92 percent (Pathman et al. 2004), confirming that recruiting participants closer to the end of their training, or closer to the time of starting practice, will result in higher completion rates.

2.3.1 Projection Bias and Financial Incentive Programs

The differences in completion rates among programs that require commitment near the beginning of training versus those that require commitment shortly before individuals begin practicing may be explained by projection bias. The differences in timing of the decision to participate between student-targeted and professional-targeted

programs may lead to a greater likelihood of projection bias among student-targeted programs. It is likely that students participating in student-targeted incentive programs believe that their preferences for primary care specialties (or other professions eligible to receive funds) and for working in a nonmetropolitan, underserved community will be the same upon completion of their training. However, individuals may fail to account for how their preferences may change over the course of several years and are more likely to exhibit biased predictions of their future tastes the further into the future they are predicting.

2.4 Relevant Causes of Projection Bias

2.4.1 Insensitivity to Temporal Location

Increasing the length of time between making a decision and experiencing the consequences of that decision contributes to a higher probability of projection bias. People do not always know what their preferences will be in the future, because it is cognitively demanding for people to imagine their tastes, and individuals are likely to make the most incorrect predictions about their future tastes when the temporal gap is long (Kahneman and Thaler 2006). Individuals create mental representations of future events, called simulations, in order to imagine consequences about an event that has not yet occurred (Gilbert and Wilson 2007). People use their immediate reactions to these simulations to predict their reactions or preferences when the event comes about. However, errors in prospection occur because not all features of an experience are included in the simulation, even though some of these excluded features may have a profound impact on the future experience. For example, a young couple that imagines the joy of owning their own home but fails to imagine the burden of home repair or yard

upkeep may overestimate how much they will enjoy home ownership. The tendency of individuals to neglect certain features of an event increases as the event becomes more temporally distant (Gilbert and Wilson 2007).

Imagining individual preferences months or years into the future increases the probability that an error in prediction will occur. Gilbert, Gill and Wilson (2002) suggest that people consider the temporal location of events only after first imagining the events happening in the present. Because individuals are insensitive to length of time, predictions of future preferences and associated utility are strongly anchored on present states.

2.4.2 Salience of Outcome Attributes

Anchoring to preferences in the present psychological state causes errors of predicted preferences if one aspect of an outcome is salient at the time the decision is made but a different aspect is prominent when the decision is experienced (Kahneman and Thaler 2006). For example, when purchasing a gym membership, the health benefits of exercising are salient at the time of purchase, but when making the decision of whether or not to exercise at the gym, other factors such as time constraints or level of motivation may be more influential in deciding whether or not to actually exercise. Forecasts about future preferences that are based on some attribute of an outcome, such as health, are likely to be incorrect if the same attribute is not focused on at the point in time in the future when the decision is being carried out.

If, for example, the attribute of receiving a significant financial incentive in the near future is salient when agreeing to participate in the SLP, but is no longer salient in the future when making practice location decisions, it is more likely that the provider will

default on their obligation. In the LRP, the incentive is more likely to be salient when recipients carry out their obligation, as it's received during the contract fulfillment. Ensuring that the benefits and costs of participation are considered when enrolling and carrying out service obligations has potential to decrease projection bias.

2.4.3 Underappreciating Adaptation

In addition to underappreciating how one's preferences will change when his or her visceral state – i.e., hunger, anger, cravings – changes, individuals also underestimate their ability to adapt to major life events. This misestimation of how one adapts can cause bias in predicted preferences or quality of life expectations. Psychological research consistently shows that individuals underestimate their ability to adapt to adversity (Halpern and Arnold 2008). Gilbert et al. (1998) examined a variety of situations where individuals overestimated the duration and intensity of their reaction to negative events. Assistant professors overestimated the impact that approval or denial of tenure would have on their life (after comparing to reports of former assistant professors), patients on a kidney transplant list overestimated the impact of denial or approval of an organ transplant, and students who had yet to experience a romantic break-up anticipated their sadness would last longer than what was reported by those who had experienced a romantic break-up. Similar results were found in situations for job seekers being rejected by a potential employer, losing a political election, and receiving negative feedback, suggesting that individuals overestimate the length of their reaction to adverse events (Gilbert et al. 1998). In general, individuals have biased expectations about the duration and intensity of emotions due to underappreciating the ability to adapt with time.

Adaptation is the process of adjusting to new or changed circumstances, and can include cognitive adaptation, such as changes in goals or interests (Dolan and Kahneman 2008). In the case of healthcare financial incentive programs, individuals may underappreciate how their interests in various specialties or preferences for practice locations will change over time as they encounter new experiences. However, prompting individuals to more carefully consider their future preferences may reduce projection bias.

In emotional adaptation experiments conducted by Ubel, Loewenstein and Jepson (2005), the researchers asked participants to estimate their quality of life associated with paraplegia before and after an adaptation exercise. They found that asking individuals to reflect on how they would adapt to becoming paraplegic over time led to increased—and less biased—quality of life estimates. Further, results indicated that the greater attention drawn to the process of adaptation, the greater the impact the adaptation exercise had on individual responses.

2.5 Program Design Elements

Some incentive programs have stipulations to increase the likelihood of completing service obligations, such as hefty financial penalties for defaulting. Bärnighausen and Bloom (2009a) determined that the proportion of participants who fulfilled their service obligation did not differ significantly between programs that did impose a cost for defaulting and those that did not. The authors suggest that this indicates participants who default on their obligation make the decision to do so independently of the conditions of the program they are enrolled in. However, contrary to this finding, Pathman et al. (2004) found that the cost of buyout among *student*-targeted incentive

programs was related to completion rates. The researchers report that very high default costs appear to cut default rates by one-third (Pathman et al. 2004a). Student-targeted programs experienced 80 percent completion rates by charging penalties three times the amount of support provided, compared to less than 50 percent completion rates for the programs with lesser default penalties. Although default costs appear to decrease default rates among student-targeted programs, these costs were also associated with lower satisfaction and shorter retention. While the researchers did not examine the influence of changing default costs within programs, Pathman et al. (2004a) found no relationship between completion rates and default cost within loan repayment programs.

Additional strategies to increase the probability of program completion include targeting individual characteristics for recruitment. One commonly used strategy is to select program candidates based on characteristics believed to be associated with a high probability of completing service obligations. There is strong evidence that healthcare providers from nonmetropolitan, or shortage area, backgrounds are more likely to choose to practice in these areas compared to their urban peers (Daniels et al. 2007 and Rabinowitz et al. 2001), and Hensel et al. (2007) estimated that nonmetro physicians are four to five times more likely to have grown up in a nonmetro community compared to physicians with a metropolitan background. Additionally, individuals with a nonmetropolitan upbringing who participate in incentive programs may be less likely to exhibit projection bias, resulting in higher completion rates, as they are more easily able to model their future preferences for living in a shortage area compared to an individual who has not lived in a rural area. Gilbert and Wilson (2007) support this claim, stating that memories are the building blocks of simulating one's reaction to future events.

In a study conducted at the University of Kentucky College of Medicine, researchers reported that the strongest predictor of student interest in nonmetropolitan practice locations was a positive opinion of the quality of life in these areas (Curran and Rourke 2004). Curran and Rourke (2004) discussed that opinion and attitude about life in nonmetro areas can be influenced by experiences of growing up in nonmetro areas, frequent exposure to practicing in these settings while in medical training, and encouragement from faculty and institutions to pursue primary care related fields.

2.6 Retention

Service-requiring programs aid in recruiting healthcare providers into underserved regions, but to reduce the long-term prevalence of these healthcare disparities it is important for providers to remain practicing in these areas. The proportion of service-requiring program participants who remained in underserved areas after completing their obligation³ ranged from 12 percent to 90 percent across eighteen retention studies reviewed by Bärnighausen and Bloom (2009a). The longest retention by program type was held by loan repayment participants—nearly 80 percent remained in their service site five years after beginning service, and 66 percent remained after eight years. Shorter retention was found for scholarship participants, with around 50 percent remaining in their service site five years after starting work there (Pathman et al. 2004b).

Research demonstrated that participants in financial incentive programs were less likely than non-participants to remain in their first underserved practice area (Pathman, Konrad, and Ricketts 1992; Pathman, Konrad, and Ricketts 1994). However, participants

³ The length of obligation and definition of retention varies across programs. Therefore, the percentages reported indicate the proportion of participants who remained in their service obligation location beyond the time stipulated by their contract.

were more likely to practice in some underserved area or to work with an underserved population compared to their non-participating peers over the long run (Bärnighausen and Bloom 2009a). The literature discusses many factors that contribute to heightened retention, such as workplace fit, community satisfaction, and familial satisfaction. Studies have found that demographics and backgrounds of incentive program participants are not related to how satisfied they are in a nonmetro or underserved area, or how long they remain practicing in their initial shortage area (Singer et al. 1998 and Pathman et al. 2004).

These findings suggest that the types of incentives used to retain doctors in underserved areas may differ from incentives designed to recruit them (Buykx et al. 2010). Li et al. (2014) conducted choice experiments among nonmetropolitan general practitioners in Australia and found that increasing the availability of a substitute general practitioner would have the largest impact in improving retention of physicians in isolated areas, followed by increased retention payments and additional compensation for complex services and geographic isolation from specialists.

CHAPTER 3: THEORETICAL FRAMEWORK

A fundamental assumption of neoclassical economics is that individuals are rational beings who make choices that maximize utility. However, findings from behavioral economic research provides evidence that individuals do not always make decisions that yield maximized utility over time, in part because they fail to consider or accurately predict what their tastes and preferences will be in the future, and instead rely heavily on current emotions or recent events in making decisions (Hsee and Hastie 2006).

Standard economic theory requires that individuals know the distribution of their preferences throughout time, yet behavioral economic evidence suggests otherwise. For example, hungry shoppers are more likely to purchase high-calorie foods compared to satiated shoppers (Tal and Wansink 2013); individuals are more likely to return warm clothing if the items were ordered on a day that was colder than when the items were received (Conlin, O'Donoghue, and Vogelsang 2007); and many purchasers of annual gym memberships quit going to the gym within a few months (Della Vigna and Malmendier 2006). These examples demonstrate that preferences change and that individuals imperfectly predict their changing preferences. Psychological evidence supports that individuals understand qualitatively the direction of their changes in preferences – e.g., being diagnosed with a chronic illness will decrease one's quality of life – but individuals systematically misestimate the magnitude of these changes (Brickman, Coates, and Janoff-Bulman 1978; Gilbert et al. 1998; Ubel, Loewenstein, and Jepson 2005).

Failure to accurately predict future preferences undermines the quality of decisions that people make (Loewenstein 2005), and may have serious health and

economic implications. The existing literature discusses the causes of projection bias and identifies its prevalence across economic decisions and domains. Loewenstein, O'Donoghue, and Rabin (2003) have developed a model of simple projection bias, and this chapter proposes an adaptation to this model by introducing a term expected to decrease individuals' propensity to exhibit projection bias. Additionally, this chapter presents hypotheses about projection bias in the context of the incentive programs and discusses which variables within this analysis are expected to be related to projection bias among participants of healthcare financial incentive programs.

3.1 Rationale for Modifying Simple Model of Projection Bias

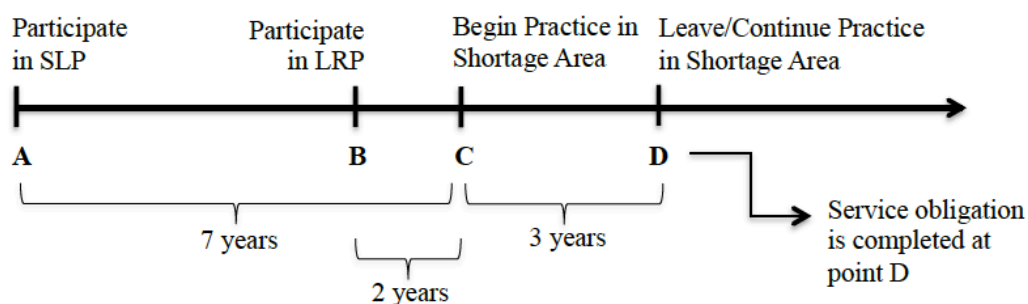


Figure 3.1: Timeline for Decisions

The general decision timeline for participating in the SLP or LRP and for completing service obligations is described in Figure 3.1. The length of time between each decision point is representative of an average medical student or licensed physician. Upon entering professional school at time period A, individuals can choose to participate in the SLP program in exchange for practicing in a shortage area beginning at time period C. During the latter part of training, participants face the decision to participate in the LRP at time period B. At point D, participants will have completed their service-obligation. If participants fail to practice in a shortage area for the length of time required by their contract, illustrated as the length of time between periods C and D, they incur a

default cost, c . This cost depends upon the default cost condition imposed during their participation.

The objective of healthcare financial incentive programs is to recruit healthcare providers to practice in areas with a low provider-to-population ratio. Thus, having participants fulfill their practice obligation – i.e., reach point D on the timeline in Figure 3.1 – is the desired outcome of such programs. Because participants choose to participate in these programs at point A or B and do not experience the consequences of their decision until point C, it is important to consider how their preferences may change over time, and how these changes influence the likelihood of a completed program outcome.

In order to increase the likelihood of a completed program outcome, reducing the propensity of projection bias exhibited among participants should help reach this desired outcome. I expect that projection bias is higher when a decision is perceived to be less binding because one would expect individuals to spend less time and cognitive resources considering the consequences of their decisions when there is no or little cost to being wrong. Alternatively, I expect the magnitude of projection bias to decrease when a decision is perceived to be more binding, encouraging individuals to carefully consider their future preferences. Ubel, Loewenstein and Jepson (2005) found that prompting individuals to think about how they adapt to changes over time led to a reduction in bias, indicating that the more individuals are prompted to consider how their preferences will change over time, the less likely they are to make biased predictions regarding their future.

I propose that both monetary and non-monetary program elements can affect the probability that projection bias occurs. The cost of defaulting on a practice obligation

may influence the likelihood of projection bias occurring by encouraging individuals to devote more effort to predicting future preferences. Regular reminders of practice obligations from program administrators are likely to maintain the salience of incentive attributes. The SLP generated three different default cost conditions where some participants faced higher default costs than others (see Table 1.1). I anticipate that the default cost, along with receiving letters reminding participants of their service obligation, contributes to the perception of how binding it is to participate in these financial incentive programs. I propose that the more costly it becomes to mispredict one's future preferences, or the more bound one feels to fulfilling their obligation, the less likely they are to exhibit projection bias and default on their obligation. Therefore, the perception of how binding the choice to participate in an incentive program is will affect the occurrence of projection bias among participants. I therefore propose an adaptation to the model of projection bias to include a variable that captures the perceived cost—at the time of the initial decision—of incorrectly predicting one's future preferences.

3.2 Modified Model of Projection Bias

The decision to participate in a financial incentive program depends upon how much relative utility individuals expect to derive from the decision to participate in the incentive program versus not participating. The model of projection bias developed by Loewenstein, O'Donoghue, and Rabin (2003) uses state-dependent utility given by $u(c_\tau, s_\tau)$, where c is consumption and s is the psychological "state" that parameterizes their preferences in period τ . Fully rational individuals are able to correctly predict their future preferences and make decisions while in current state s' that maximize their predicted

utility. For individuals who correctly predict their future preferences, predicted utility is equal to their true utility, $\tilde{u}(c, s | s') = u(c, s)$. Individuals exhibiting projection bias also attempt to maximize utility; however, true future utility will differ from current and predicted utility due to the influence of projection bias.

Loewenstein, O'Donoghue, and Rabin's (2003) model of projection bias posits that predicted utility is a weighted combination of true future utility and current utility using weights of α and $(1 - \alpha)$, where the magnitude of projection bias is denoted by α . Accordingly, there exists an $\alpha \in [0, 1]$ such that for all c, s , and s' , $\tilde{u}(c, s | s') = (1 - \alpha) u(c, s) + \alpha u(c, s')$. Because α is a value between 0 and 1, predicted utility will fall somewhere between current utility and true utility in the future. If $\alpha = 0$, individuals predict their future preferences accurately and no projection bias occurs. When $\alpha = 1$, individuals predict that their future preferences are identical to current preferences. As α tends to 1, more projection bias occurs.

I propose that a binding variable, β , which represents how binding a decision is perceived to be, will influence the magnitude of projection bias, represented by α , by affecting the cognitive resources invested in envisioning future preferences. Thus, the projection bias parameter is a function of how binding the decision is— $\alpha(\beta)$ —where $\alpha' < 0$. With this adaptation, predicted utility in the presence of projection bias is now denoted by

$$\tilde{u}(c, s | s') = (1 - \alpha(\beta)) u(c, s) + \alpha(\beta) u(c, s'). \quad (1)$$

For the utility derived from healthcare financial incentive programs, I propose that utility is a function of the value of incentive received described by μ , the perceived utility of practicing in a designated shortage area described by γ , and the actual utility of

practicing in a shortage area described by ε , which is unknown at the time of making a participation decision, given a person's current state, s' . Thus, utility is denoted as $u(\mu, \gamma, \varepsilon | s')$. A similar utility function has been used by Conlin, O'Donoghue, and Vogelsang (2007) to test the presence of projection bias in catalog orders for cold weather clothing. Now, applying the binding variable to the predicted utility model for healthcare provider incentive programs, predicted utility is denoted by

$$\tilde{u}(\mu, \gamma, \varepsilon, s | s') = (1 - \alpha(\beta)) u(\mu, \gamma, \varepsilon, s) + \alpha(\beta) u(\mu, \gamma, \varepsilon, s'). \quad (2)$$

If participants believe their decision to participate is binding, which is a function of their default condition, it is likely they will spend more time predicting what their true preferences will be for working in a shortage area, decreasing the magnitude of projection bias and increasing the likelihood participants will complete their service obligation.⁴

After individuals choose whether to participate in the program, the next decision of consequence that they make, which is observed in the data, is whether to complete their practice obligation. Intuitively, individuals will complete their practice obligation if the difference between their ideal practice location, denoted by L^* in state s , and their current utility from practicing in a shortage area (SA) in state s , is less than the cost, c , incurred from defaulting on their contract, described by

$$u(L^* | s) - u(SA | s) < c. \quad (3).$$

It is possible for an individual's ideal practice location to be in a shortage area, in which case the left side of the equation would equal zero. This equation suggests that even if a

⁴ Embedding this model into an intertemporal choice scenario was considered. However, because there is a delay in receiving the incentive in both programs, it is unlikely that individuals are exhibiting quasi-hyperbolic discounting that would result in a preference reversal in one program but not the other. Therefore, an intertemporal choice model is not critical to model decision-making in this situation.

shortage area is not one's ideal practice location preference, if the cost of default is greater than the difference in utility between their ideal location and shortage area location, they will complete their service obligation.

Conversely, individuals will default on their practice obligation if the difference between their ideal practice location in state s and their current utility from practicing in a shortage area in state s is greater than or equal to the cost incurred from defaulting on their service obligation, described by

$$u(L^* | s) - u(SA | s) \geq c. \quad (4)$$

If an individual's ideal location provides a much higher level of utility than the shortage area location, it may be preferable to incur the cost of default in order to relocate to their preferred location. If great enough differences in the level of utility exist between their ideal and shortage area location, individuals are likely to default on their service obligation.

3.3 Hypotheses Derived from Model

This research seeks to identify variables that contribute to or detract from the likelihood of exhibiting projection bias among individuals participating in healthcare financial incentive programs. The following hypotheses, derived from the models above, discuss what variables I expect to exacerbate or counteract the forces of projection bias in healthcare financial incentive programs.

First, I expect that changes in monetary and non-monetary elements of the default conditions will increase participants' efforts in predicting future preferences and will decrease the likelihood of projection bias. Thus, in my first hypothesis (HP1), I expect participants in default condition two (DC2) and default condition three (DC3) will be less

likely to default on their service obligation because they perceive the commitment to participate to be a more binding decision. Since participants in default condition one (DC1) did not receive semi-annual reminders, they therefore may have felt that their commitment was less binding compared to those who did receive semi-annual letters, reminding them of their obligation and the cost of default until their obligation was fulfilled. The default condition influences how bound the participant feels to their decision to participate, affecting β in equations one and two. Equations three and four also suggest that changes to the cost of default, c , may make individuals less likely to default on their service obligation, increasing the likelihood of a completed outcome. While perceived higher default costs could decrease the number of individuals participating in the programs overall, those who do participate after carefully considering their future preferences, induced by a more binding contract, are less likely to exhibit higher levels of projection bias. Therefore, I expect that changes to the default cost will lead to higher probability of participants completing their service obligations.

The value of the incentive received is directly related to the utility of participating in the SLP and LRP. The nominal value of the incentive has changed over time within both programs. While the nominal value changed at specific times in both programs, the real value of the incentives has varied in every year. In hypothesis two (H2) I anticipate that the higher the incentive value, the greater the magnitude of projection bias and the more likely one is to default on their service obligation. If the value of the incentive rises, increasing the utility of participating, enrolling in a program may become more enticing to individuals who would otherwise be unlikely to consider practicing in a shortage area. Higher incentive values may also make this aspect of the program more salient, and the

difference in timing of the receipt of benefits may differentially affect continued attribute salience in the two programs. In the LRP, program benefits should still be salient while they are participating because they receive the benefits at that time, while SLP participants' benefit levels are no longer salient at the time they decide whether or not to default. Although increased incentive values may increase the total number of participants in the program, I anticipate it will increase the likelihood of projection bias, as individuals who may not have a true preference for practicing in shortage areas are participating, and are doing so based on the financial incentive it provides⁵.

In hypothesis three (H3), I anticipate that participants of incentive programs who grew up in nonmetropolitan communities and are more familiar with the realities of living in these areas are less likely to exhibit biased projections of their anticipated utility for practicing in a nonmetropolitan areas and are therefore less likely to default on their service obligation. I make this prediction because choices informed by personal memory or experiences are more likely to result in accurate predictions of future preferences (Kahneman and Thaler 2006). Alternatively, I expect that participants who grew up in larger communities – i.e., micropolitan and metropolitan areas – are more likely to exhibit projection bias and default on their service obligations. Individuals with previous experiences in shortage area locations, including nonmetropolitan areas, are more likely to accurately predict their preferences in their future state, *s*, resulting in a higher quality participation decision.

⁵ A higher incentive value also has the potential to exacerbate present-biased preferences. Individuals who exhibit present-biased preferences trade off earlier vs. delayed benefits (or costs) differently depending on how immediate the incentive is received. Those who exhibit present-biased preferences give stronger relative weight to the earlier benefit as it approaches in time (O'Donoghue and Rabin 1999). Participants may experience heightened present-biased preferences by receiving larger monetary incentives.

Within the SLP, I hypothesize (H4) that longer training periods are likely to exacerbate projection bias and therefore the probability of default. The greater the temporal gap in deciding to participate and carrying out the decision, the greater the probability that inaccurate predictions about future preferences are made, and thus, the greater the probability of default. Figure 3.1 helps to visualize the time gap between an individual's current state, s' , when they make the decision to participate at points A or B and their future state, s , at point C when their service obligation is carried out. Because the temporal gap between the decision to participate and carrying out the decision is much shorter in the LRP and does not differ among professions, I expect longer training periods to only influence projection bias among participants of the SLP.

Gender could also influence one's current or future state, and thus has the potential to influence one's predictions of future preferences. There is much media attention given to the differences in work and familial roles taken on between men and women. The Pew Research Center (2015) reports that women adjust their careers more than men to meet familial needs. Additionally, a study by Field and Lennox (1996) found that gender affects future career choices and that a cohort of women in medicine indicated their career choice is influenced by their desire to have a family in the future. In a study concerning gender-related factors in recruiting rural physicians, Ellsbury et al. (2002) found that women were significantly more likely than men to attribute more importance to opportunities for their partner or spouse, the availability of child-care, and flexible scheduling in making practice location decisions. Thus, it is possible that women who participate in a financial incentive program may be more likely than men to change their original plans of practicing in a shortage area in favor of accommodating a partner's

location preferences or for other familial considerations. Therefore, in hypothesis five (H5) I anticipate that men are less likely to exhibit projection bias compared to women, as men are less likely to change or adjust their career plans to meet familial needs.

3.4 Variables Used to Test Hypotheses

The variables used in this research are common among studies that describe the effectiveness of recruitment and retention of healthcare financial incentive programs (Rabinowitz et al. 2001; Jackson et al. 2003; Pathman et al. 2004a; Pathman et al. 2004b; Daniels et al. 2007). Additionally, these variables capture characteristics of participants or the state of the program under which individuals participated to provide insight into the state, s' , of participants.

The default cost condition under which individuals agreed to participate in the incentive programs helps to capture how bound a participant may feel to their commitment to practice in a shortage area. These conditions are estimated based on the incentive program start date and anticipated graduation date articulated in the data. These estimates also were used to identify the nominal incentive value individuals received.

Additionally, the research uses population of the town from which participants graduated high school to capture experience in nonmetropolitan areas. The analysis categorizes these hometown populations into noncore (populations less than 10,000), micropolitan (populations between 10,000 and 50,000), and metropolitan (populations greater than 50,000) communities.

Length of training (LOT) captures the temporal gap between when a participant chooses to participate in the SLP or LRP, at points A and B in Figure 3.1, and when the decision is actually carried out, represented by point C. Length of training is estimated

based on the individual's career and specialty – e.g., medicine, dentistry, physician assistant – and the average length of training, including education and residency training, required of the particular career.

CHAPTER 4: SUMMARY STATISTICS AND DATA

4.1 Sample

Panel data were collected from the Health Professions Tracking Service (HPTS), an annually updated repository maintained by the College of Public Health at the University of Nebraska Medical Center (UNMC). In operation since 1995, the HPTS database maintains Nebraska's licensed healthcare professionals. It is kept up to date by annually surveying Nebraska healthcare providers as well as semi-annually surveying practice location administrators. The combined provider and practice location survey responses allow the HPTS to link the provider and practice location data in a relational database (UNMC Center for Health Policy 2012). The HPTS tracks essential information on licensed healthcare providers in Nebraska including profession, specialty area, practice locations and dates of practice in each location, city of high school graduation, gender, participation in the State of Nebraska Rural Incentive Programs, as well as the program outcome – e.g., completed or defaulted. The HPTS works collaboratively with the Nebraska Department of Health and Human Services, which provided the dataset for this research.

UNMC's College of Public Health has compared data from the HPTS to the American Medical Association (AMA) Physician Masterfile, a database commonly used for researching the supply of physicians as well as recruitment and retention rates of physicians who have participated in federal or state incentive programs (UNMC Center for Health Policy 2012). In a comparison study conducted by UNMC, physician supply estimated by the AMA Physician Masterfile is up to 30 percent greater than the supply reported by the HPTS. The HPTS is likely to report a more accurate picture of the supply

of healthcare providers in Nebraska, as it accounts for hours worked per week and is updated annually.

The sample collected from the HPTS contains 758 observations and includes participants from the SLP and LRP. The sample includes 261 individuals who participated in the SLP between 1979 and 2015 and 489 who participated in the LRP between 1994 and 2015. The summary statistics found in Table 4.1 reflect this sample of participants. Additionally, eight individuals participated in both programs, and are not included in the SLP and LRP counts. The data encompass all healthcare professions eligible to receive funds from the Nebraska Rural Incentive Programs: physicians, nurse practitioners, physician assistants, dentists, clinical psychologists, licensed mental health practitioners, pharmacists, occupational therapists, and physical therapists. All individuals in the dataset are past or current participants of the SLP or LRP who have practiced in Nebraska.

Supplemental data were collected to enhance the information provided by the HPTS. Data on Nebraska town populations were imported from the 1970 through 2010 U.S. Censuses. Additionally, the OMB designations of Nebraska counties were imported from the Office of Management and Budget. This information was used in determining the population size and the metro- or non-metro- designation of the high school graduation city of each program participant, helping to capture the experience or familiarity individuals have of living in a non-metro location. Additionally, the OMB designation is used to classify the initial shortage area location. Also, because state shortage areas are reviewed and adjusted every three years, counties designated as

shortage areas over time were imported from the Nebraska Department of Health and Human Services.

To capture the length of time a participant spent in training, I added a length of training variable (LOT) that was estimated based on the average length of training required for the individual's profession – e.g., medicine, dentistry, physician assistant – and specialty – e.g., family practice, general surgery (All Allied Health Schools 2016; All Nursing Schools 2016; American Associations of Colleges of Pharmacy 2016; American Dental Education Association 2015; American Physical Therapy Association 2015; Careers in Psychology; Physician Assistant Education Association 2013; Washington University School of Medicine in St. Louis 2012). LOT includes professional school education as well as time spent in residency training.

To capture the conditions under which individuals participated in the incentive programs, I included a categorical default condition (DC) variable and incentive value variable. Beginning practice dates and anticipated graduation dates were used to estimate what default and incentive value conditions applied to participants when they started the program. Table 4.1 provides the number of individuals participating under each default and incentive condition. Note that in default condition three in the SLP, approximately two-thirds of subjects in this period have yet to reach a program outcome and are therefore excluded from the analysis. Thus, results regarding this variable may not reflect the long-term results of this default condition.

For both the SLP and LRP, I adjusted nominal incentive values into real values to capture the changes in the real value of the incentive, under the assumption that individuals received the maximum incentive value in each program per year. The

adjusted incentive value (AIV) is the incentive variable used in the analysis. A summary of the nominal value of incentives and eligible recipients is summarized in Table 4.2. Within the SLP from 1979 to 1990, the incentive was a low-interest loan for medical students. Because I am interested in the relative effect of incentive values, I code the monetary value of the low-interest loan as zero. While this incentive undoubtedly provided positive monetary benefit, I made this specification in order to include these participants in the regression, as nearly half of SLP participants participated under this incentive condition. Furthermore, SLP participants who received a forgivable student loan would have also experienced savings due to foregone interest expenses, which is unknown and unaccounted for. Therefore, even after specifying the incentive value as zero for SLP participants who received a low-interest loan, the analysis accurately compares relative values across incentive conditions.

The duration of practice (in months) in one's initial shortage area is also calculated based on practice location start and end dates. The data used in the analysis only include participants who have completed or defaulted on their service obligation. This variable captures the length of time participants remain in their initial shortage area, and will be used in the survival analysis. Table 4.4 presents the proportion of initial shortage area locations by OMB classifications. Table 4.5 provides the mean and median duration of practice in the initial shortage area as well as the standard deviation of SLP and LRP participants.

The sample in this study is limited to participants of the State of Nebraska Rural Incentive Programs. Healthcare providers who have participated in federal incentive programs, such as the National Health Service Corps, were not included in this study.

Additionally, I exclude program participants who have not yet completed or defaulted on their obligation. Thus, current students and residents are excluded from the sample because they have not yet reached a program outcome of completed or defaulted. Similarly, if a participant is licensed and currently practicing under obligation, but has not yet arrived at a program outcome, the participant is excluded from the analysis. With these exclusions, the sample includes 615 observations, 220 in the SLP and 395 in the LRP.

In the survival analysis, I only include participants who started practice after the HPTS began systematically tracking provider practice locations and duration. In other words, participants who began practicing prior to 1995, the year the HPTS started tracking provider locations, are excluded from this regression. This ensures accuracy of the data used in the analysis. Furthermore, recall that the survival analysis only includes participants who have reached a completed program outcome. This ensures that the length of time spent in one's initial practice location was a shortage area. With these exclusions, the survival analysis sample includes 276 observations.

Table 4.1

Summary Statistics

	SLP n=261	LRP n=489
Participants by Default Condition 1: 24% interest ('79-'97) 2: 24% interest & semi-annual letter ('98-'06) 3: 150% principal + 8% interest & semi-annual letter ('07-'15) 4: 125% funds received ('94-'15)	1: 142; 54.4% 2: 59; 22.6% 3: 60; 23.0%	4: 489; 100%
Participants by Incentive Conditions 1: Low interest loan ('79-'90) 2: 10K, 5K ('91-'98) 3: 20K, 10K ('98-'15) 4: 20K, 10K ('94-'05) 5: 40K, 20K ('06-'15)	1: 94; 36% 2: 48; 18.4% 3: 119; 45.6%	4: 234; 47.8% 5: 255; 52.1%
Program Outcomes (2 outcomes unknown in SLP)	Default: 114; 43.7% Complete: 106; 40.6% In Practice: 16; 6.1% In Training: 23; 8.8%	Default: 41; 8.4% Complete: 354; 72.3% In Practice: 94; 19.2%
Profession	Medicine: 170 PA: 25 Dental: 33 Mental Health: 33	Medicine: 150 PA: 116 NP: 53 Dental: 26 Mental Health: 39 OT: 40 PT: 31 Pharmacy: 34

Table 4.2

Nominal Incentive Values and Eligible Recipients

Program	Time Period	Nominal Incentive Value	Eligible Recipients
SLP	1979-1990:	Low-interest loan	Medical students
	1991-1997	\$10,000	Medical students
		\$5,000	Physician assistant students
	1998-2015:	\$20,000	Medical and dental students
		\$10,000	Physician assistant and graduate-level mental healthcare students
LRP	1994-2005	\$20,000 \$10,000	Physicians, dentists, psychologists, nurse practitioners, physician assistants, licensed mental health practitioners, pharmacists, occupational therapists, and physical therapists
	2006-2015	\$40,000 \$20,000	

Table 4.3

Percentage of Initial Service Obligations by OMB Designation

SA Type	% Of Initial Service Obligations
Metropolitan	4.4%
Micropolitan	28.8%
Non core	66.8%

Table 4.4

Mean and Median Months in Initial Shortage Area by Program Type

Program Type	Mean	Median	Standard Deviation
SLP	55.28	37.00	36.79
LRP	70.47	53.00	52.40

CHAPTER 5: EMPIRICAL MODEL

5.1 Probit Model

I use a probit model to analyze participants' program outcomes. A probit model is appropriate because the program outcome variable is binary, or has two possible outcomes. Participants either complete or default on their service obligation. The purpose of this model is to determine what observable explanatory variables increase the probability of a completed program outcome, leading to insight on what variables may contribute to or counteract the forces of projection bias. The model considers characteristics of the SLP and LRP programs, as well as variables unique to program participants.

The dependent variable is a binary measure of the program outcome, and captures whether the participant *completed* or *defaulted* on their service obligation. If a participant completed their service obligation in the SLP, they practiced in a state-designated shortage area for the same number of years they received the incentive. If a LRP participant completed their service obligation, they practiced for three years in a state-designated shortage area. If a participant defaulted on their service obligation, they may have defaulted while in school or residency if participating in the SLP, or after spending some amount of time in a state-designated shortage area, but less than what is required of their obligation in the SLP or LRP.

I analyze the data for each program separately and then in a pooled analysis. The model includes independent variables including default condition (DC), adjusted incentive value (AIV), length of training (LOT), gender (male), the categorical population of their hometown, and an error term, which is normally distributed in a probit

model. The justifications of these variables are discussed in Chapter 3. The probit model for this analysis is described by

$$\begin{aligned} Outcome = & \beta_0 + \beta_1 * Default\ condition + \beta_2 * Adjusted\ incentive\ value + \beta_3 \\ & * LOT + \beta_4 * Gender + \beta_5 * Hometown\ Population + \varepsilon. \end{aligned}$$

It should be noted that in regressions involving the LRP, the default condition variable changes to a time period variable, as the default cost remained constant. The time periods are reflective of the same time frame as the default conditions in the SLP program. Following this time period schedule allows for comparisons between SLP and LRP participants who participated during the same time period.

In the pooled analysis, I include a program type – i.e., SLP – variable. In a second variation of the pooled regression, I include interaction terms between the SLP and TP and SLP and LOT. These interactions were selected because previous studies suggest the temporal gap, which differs between programs, is likely to increase bias, as well as to capture the influence of default cost changes over time in the SLP. The interactions allow for understanding and comparison of the relationship between the program type and variables that are expected to influence the magnitude of projection bias among participants. The interacted probit model is described by

$$\begin{aligned} Outcome = & \beta_0 + \beta_1 * Program\ Type + \beta_2 * Adjusted\ incentive\ value + \beta_3 \\ & * LOT + \beta_4 * Gender + \beta_5 * Hometown\ Population + \beta_6 \\ & * Time\ Period + \beta_7 * Program\ Type * Time\ Period + \beta_8 \\ & * Program\ Type * LOT + \varepsilon. \end{aligned}$$

5.2 Survival Analysis

I conduct a survival analysis to model the length of time in months spent in the initial shortage area location among participants who completed their service obligation. Survival analysis is appropriate because it is used to analyze duration data, or how long until an event occurs. In this research, the duration measured is the number of months spent in one's initial shortage area location until they exit to a new location. Using a Kaplan-Meier survival function, I compare survival probabilities between SLP and LRP participants to determine if there is a significant difference in the survival proportion by program type. However, a Kaplan-Meier survival function only allows comparison of one variable (in this case, program type) and fails to take into account other variables that may influence the length of survival in a shortage area, so further analysis must accompany these results.

Next, I conduct a Cox regression analysis to observe associations between variables and survival. The dependent variable is the hazard – i.e., the probability of leaving the initial shortage area. The predictor variables used in this regression are the same as those used in the aggregated probit model – program type, adjusted incentive value, time period of participation, LOT, gender, and the categorical variable of hometown population. The Cox regression helps distinguish individual contributions of these variables on the probability of exiting the initial practice location.

Conducting a survival analysis provides insight into what variables may influence projection bias after entering and practicing in a shortage area location. It is possible that individuals exiting their initial shortage area upon completion of their service obligation over-estimated their experienced utility of practicing in a shortage area, at least compared

to those who remained in their initial location beyond the time required of them. While it is possible these participants exited their initial shortage area for a different shortage area, the analysis does not test for this.

Because the survival analysis excludes participants who defaulted on their service obligation, or individuals who exhibited early signs of projection bias, it may be more difficult to draw conclusions about what variables influencing the hazard of exiting the initial location are caused by projection bias, rather than other external determinants of retention including family, community, and practice satisfaction.

CHAPTER 6: RESULTS & DISCUSSION

6.1 Results

6.1.1 Probit Model

Results for the probit model regression for the SLP program are provided in Table 6.1. Results show that LOT is strongly significant and therefore the longer an individual spends in training, the more likely they are to default on their SLP service obligation. Additionally, SLP participants in default condition three (DC3) are more likely to default on their service obligation, which is significant at the 5 percent level. Participants in default condition two (DC2) are less likely to default, although this is not statistically significant. While not significant, the gender (male) coefficient is negative indicating that males may be less likely than females to default in the SLP. The hometown population coefficients are both positive, indicating that those who grew up in a micropolitan or metropolitan area are more likely to default on their obligation compared to those whose hometown is a nonmetropolitan, noncore area. Overall, the SLP probit model supports that longer training periods result in greater likelihood of projection bias (H4). Although insignificant, the direction of the coefficients align with hypotheses regarding AIV (H2), hometown population (H3), and gender (H5). The prediction that changes to the cost of default will decrease default rate (H1) is not strongly supported in this model, as DC3 is positive and significant, although DC2 moves in the opposite direction.

The probit model for LRP uses the same variables as the SLP model, but recall that the time period variables now reflect the time frame of the SLP default conditions changes, as discussed in Chapter 5. This variable captures any unobserved forces influencing default during the different time periods. Results for this model are found in

Table 6.2. Significance for time period two (TP2) is found at the 5 percent level. Thus, LRP participants from 1998-2006 are less likely to default on their service obligation. Note that the gender (male) coefficient is negative in this model and approaching marginal significance, lending some support for H5. The remaining variables show no significance, which is likely due to differences in LRP program design that reduce the likelihood of projection bias. Thus, it is unlikely the any changes made to the structure of this program will influence program outcomes in a meaningful way.

Next, I analyzed the aggregated data on participants of both programs. By aggregating the samples, statistical comparisons can be made between the two programs. Results for the uninteracted aggregated probit model can be found in Table 6.3. A second model interacts the SLP with LOT and time periods two (TP2) and three (TP3). Results for the interacted aggregated probit model can be found in Table 6.4.

Based on the uninteracted model, SLP program participants are significantly more likely than LRP participants to default on their service obligation. LOT is marginally significant, indicating that the longer the training of an individual in either program, the more likely they are to default on their service obligation, supporting H4. The gender (male) variable is also slightly significant, suggesting that men are less likely to default on their service obligation (H5).

In the interacted model, the interaction between SLP and LOT shows significance at the 1 percent level. This indicates that participants of the SLP with longer training periods are more likely to default on their obligation compared to LRP participants of similar training length. For example, a dentist in the SLP is more likely to default than a dentist in the LRP. The SLP and time period interactions are also significant, suggesting

that participants of the SLP program in both TP2 and TP3 are more likely default on their service obligation compared to LRP participants of the same time periods. The significance in these interactions further support that participants in the SLP are more likely to default than those of the LRP. Similar to the uninteracted model, gender (male) is marginally significant with a negative coefficient (H5). TP2 is significant at the 5 percent level, indicating that all incentive program participants between 1998 and 2006 are less likely to default on their service obligation.

Table 6.1

Probit Model for SLP

Coefficients	Point Estimate (Std. Error)	Pr(> z)
Intercept (β_0)	-1.336*** (0.422)	0.002
SLP DC2 (β_{11})	-0.187 (0.412)	0.650
SLP DC3 (β_{12})	0.9462** (0.460)	0.040
AIV (β_2)	0.00001 (0.00002)	0.389
LOT (β_3)	0.187*** (0.061)	0.002
Male (β_4)	-0.243 (0.215)	0.258
Hometown Population (β_{51}) 10,000 – 49,999	0.404 (0.369)	0.274
Hometown Population (β_{52}) 50,000 <	0.334 (0.423)	0.429
AIC	237.97	

Significance codes: 0.01* ; 0.05** ; 0.1***

Table 6.2

Probit Model for LRP

Coefficients	Point Estimate (Std. Error)	Pr(> z)
Intercept (β_0)	-0.586 (0.385)	0.128
TP2 (β_{11}) (1998-2006)	-0.697** (0.304)	0.022
TP3 (β_{12}) (2007-2015)	0.201 (0.352)	0.569
AIV (β_2)	-0.00004 (0.00002)	0.140
LOT (β_3)	0.115 (0.089)	0.196
Male (β_4)	-0.363 (0.243)	0.136
Hometown Population (β_{51}) 10,000 – 49,999	-0.040 (0.302)	0.896
Hometown Population (β_{52}) 50,000 <	-0.234 (0.338)	0.489
AIC	196.81	

Significance codes: 0.01* ; 0.05** ; 0.1***

Table 6.3

Probit Model for Aggregated Data

Coefficients	Point Estimate (Std. Error)	Pr(> z)
Intercept (β_0)	-1.558*** (0.269)	<0.001
Program Type: SLP (β_1)	1.262*** (0.187)	<0.001
AIV (β_2)	-0.000003 (0.000009)	0.711
LOT (β_3)	0.073* (0.039)	0.062
Male (β_4)	-0.291* (0.155)	0.061
Hometown Population (β_{51}) 10,000 – 49,999	0.101 (0.220)	0.647
Hometown Population (β_{52}) 50,000 <	-0.068 (0.245)	0.781
TP2 (1998-2007) (β_{61})	-0.190 (0.224)	0.397
TP3 (2007-2015) (β_{62})	0.416 (0.276)	0.132
AIC	437.34	

Significance codes: 0.01* ; 0.05** ; 0.1***

Table 6.4

Interacted Probit Model for Aggregated Data

Coefficients	Point Estimate (Std. Error)	Pr(> z)
Intercept (β_0)	-0.893*** (0.332)	0.007
Program Type: SLP (β_1)	-0.383 (0.534)	0.473
AIV (β_2)	-0.000003 (0.00001)	0.791
LOT (β_3)	-0.0006 (0.060)	0.992
Male (β_4)	-0.303* (0.158)	0.055
Hometown Population (β_{51}) 10,000 – 49,999	0.161 (0.223)	0.470
Hometown Population (β_{52}) 50,000 <	-0.023 (0.250)	0.927
TP2 (β_{61}) (1998-2006)	-0.615** (0.293)	0.036
TP3 (β_{62}) (2007-2015)	-0.051 (0.307)	0.869
SLP * TP2	0.770* (0.463)	0.096
SLP * TP3	1.192** (0.493)	0.016
SLP * LOT	0.205*** (0.078)	0.008
AIC	432.05	

Significance codes: 0.01* ; 0.05** ; 0.1***

6.1.2 Survival Analysis

The Kaplan-Meier survival function provides a graphical representation of survival probability between participants of the SLP and LRP program in Figure 6.1. Approximately 80 percent of participants in the SLP and LRP program remain in their initial practice location after 36 months of beginning practice there. With a p-value of 0.049, the Kaplan-Meier survival function suggests that there are differences in the

length of practice in one's initial practice location based on program type. However, this graphical representation is insufficient in determining predictors of the probability of exiting the initial shortage area location, as it does not take into account variables beyond program type. Thus, a cox hazard regression is conducted.

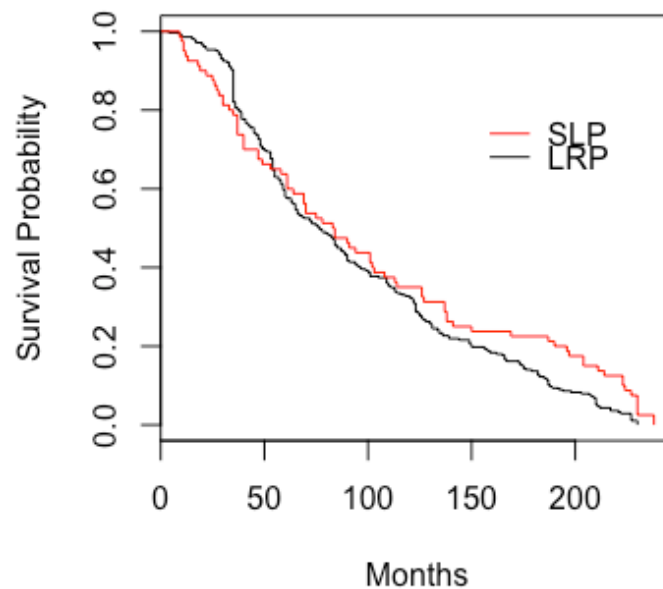


Figure 6.1: Survival Probability by Program Type

The results from the cox hazard regression, found in Table 6.5, show that TP2, TP3 and the interaction between SLP and TP3 are strongly significant. Additionally, LOT is significant at the 5 percent level and metropolitan hometown variable is marginally significant. The coefficient for TP2 and TP3 is positive, indicating that the probability of these participants exiting their initial shortage area increases, and that these participants are more likely to exit than those in TP1. For example, the hazard ratio for TP2 is 2.47. A hazard ratio greater than one indicates that participants of TP2 are exiting their shortage area faster than participants of TP1. The same is true for participants in TP3. Additionally, the coefficient for the interaction term between the SLP and TP3 is greater than one, indicating that participants of the SLP in TP3 are significantly more likely to

exit their initial practice location compared to SLP program participants in TP1. Note that in this analysis there are participants, particularly in TP3, who have yet to exit their initial shortage area, and therefore their total survival time is incomplete. These observations are called right-censored, and the cox regression correctly accounts for this type of data.

The negative coefficient of the LOT variable suggests that the probability of exiting the initial shortage area location – i.e., hazard of exiting – decreases. Thus, the longer the training, the more time an individual will stay in their initial location. For example, an individual with seven years of training compared to an individual with two years of training results in a hazard ratio of 0.64. This means that those who train for seven years are 36 percent less likely than those with two years of training to exit the initial shortage area location.

The variable for those who grew up in a metropolitan area is marginally significant with a positive coefficient and has a hazard ratio of 1.35. This indicates that participants with a metropolitan background are more likely to exit their initial shortage area compared to those with a noncore, nonmetropolitan upbringing.

Table 6.5

Cox Hazard Regression for Aggregated Data

Coefficients	Point Estimate Coefficients	Exp(coef)	Pr(> z)
SLP (β_1)	0.005	1.005	0.994
AIV (β_2)	0.000006	1.000	0.602
LOT (β_3)	-0.090**	0.914	0.044
Male (β_4)	0.098	1.103	0.437
Hometown Population (β_{51}) 10,000 – 49,999	0.130	1.138	0.481
Hometown Population (β_{52}) 50,000 <	0.300*	1.349	0.097
TP2 (β_{61}) (1998-2006)	0.904***	2.470	<0.001
TP3 (β_{62}) (2007-2015)	1.755***	5.785	<0.001
SLP * TP2	0.5240	1.689	0.246
SLP * TP3	2.618***	13.71	<0.001
SLP * LOT	0.061	1.063	0.488
R square	0.303		
Likelihood ratio test	107.8	p=0	
Wald test	113.3	p=0	
Score (logrank) test	161.9	p=0	

Significance codes: 0.01* ; 0.05** ; 0.1***

6.2 Discussion

6.2.1 Probit Model

This analysis strongly supports that SLP participants are more likely than LRP participants to default on their service obligation. There is also variation in the probability of default within the SLP based on variables that are related to the likelihood of projection bias, and results show that the longer one spends in training, the more likely they are to default on their service obligation in the SLP. For example, those with longer training periods in the SLP, such as physicians, are more likely to default compared to those whose training periods are shorter in length, such as physicians assistants.

These results indicate that SLP participants and those with longer training periods in the SLP are more prone to exhibiting projection bias. Because one of the key differences in the programs is the duration between when the incentive is delivered and when the service is carried out, which is also influenced by the length of training for SLP participants, it suggests that the temporal gap exacerbates the effects of projection bias. That is, the longer the time between making the decision to participate and fulfilling the service obligation, the more likely one is to exhibit projection bias because temporal proximity influences our ability to correctly predict or anticipate our future preferences.

Gilbert and Wilson (2007) discuss that predicting the future requires mental simulation of an event one has not experienced. In deciding to participate in an incentive program, one likely imagines or calls upon memories to predict what it would be like to practice in a shortage area. The problem, however, is that those simulations tend to omit certain features of the experience, which worsens when the event becomes more temporally distant (Gilbert and Wilson 2007). Students may not consider all aspects of practicing in a shortage area. For instance, they may spend less time considering features unrelated to practicing medicine or having their student debt paid off like having limited options of where to practice, which influences their proximity to family, having a significant other who prefers living in a city, or fewer social activities available. Predicting future preferences can also be prone to error if predictions are based on a small number of memories or previous experiences or if they lack context (Gilbert and Wilson 2007).

Not only are predictions of future preferences most likely incorrect when the temporal gap is long, there are also inaccuracies when an individual's circumstances are

changing (Kahneman and Thaler 2006). Students in the healthcare field are exposed to many facets and specialties in healthcare throughout their training. Thus, considering experiences that occur within the training period may also be contributing to the significance of the LOT and program type variable. Medical students, for example, must commit to practicing in a primary care-related field in order to receive funds through the SLP. However, a portion of their training is devoted to exploring specialty areas through rotations, including those outside of primary care. It is possible that medical students who default on their obligation do so after discovering a preference for a specialty area outside of primary care. By underestimating that specialty preferences may change over time, program participants entering fields where they have the option to further specialize may be even more prone to exhibit projection bias.

Furthermore, the benefit of the incentive may no longer be salient for SLP participants by the time they are practicing in a shortage area. Because they received the benefit while in school and are no longer receiving such an incentive when carrying out their obligation, it could increase the likelihood of SLP participants to default on their service obligation, especially if they were particularly motivated to participate due to the incentive, rather than the mission of working with underserved populations. In the LRP, program incentives should still be salient while they are practicing in a shortage area because they receive the benefits at that time. Overall, these results confirm the hypothesis (H4) that LOT exacerbates the propensity of exhibiting projection bias within the SLP.

Results do not strongly support the hypothesis that increasing the perception of how bound one is to fulfilling their obligation – i.e., by changing the cost of default – will

result in a higher probability of completion. Although not significant, DC2 in the SLP model indicates that participants in this condition are less likely to default than those in DC1. Because the financial cost of defaulting does not differ between these conditions, it suggests that sending semi-annual letters reminding participants of their obligation may have positively influenced the completion rate. However, models also indicate that those in DC3 are more likely to default, even in the presence of semi-annual letters and a default cost of 150 percent plus interest. However, two-thirds of subjects participating under DC3 have yet to reach a program outcome, and are therefore not included in the analysis. Thus, the DC3 result may not reflect the long-term outcomes of this condition.

The default condition in the LRP remained constant across time, thus the significance in the LRP model TP2 variable captures unobserved forces influencing default during this time period. Within the interacted aggregated model, participants of both programs in TP2 are less likely to default. This variable represents unobserved trends affecting the probability of default, as well as the change in the default condition in the SLP program, suggesting that this DC2 may have positively influenced the program outcome.

The aggregated interacted model also shows that participants of the SLP in TP2 and TP3 are more likely to default than LRP participants of the same time period. This further supports that SLP participants are more likely to default than LRP participants across time, even when the cost of default increased in the SLP program. While the expectation that increasing the cost of default would reduce the probability of default is not strongly supported in this data, behavioral economic research supports that prompting individuals to think more carefully about how preferences change over time results in less

biased predictions. It could be the case that semi-annual letters and the financial penalties are not explicit enough to prompt such contemplation.

The gender (male) coefficient is negative in every model specification, and is marginally significant in two of the four models. This supports the hypothesis (H5) that men are less likely than women to default on their service obligation. While the lack of significance could be due to the size of the data set, it is worthy to point out the direction of the estimate. Studies support that women are more likely than their male counterparts to change their career plans or behaviors due to familial responsibilities (Brotherton et al. 1997). These findings suggest that men may be more likely to follow-through and complete their original plans to practice in a healthcare shortage area compared to their female counterparts, indicating men may be less prone to exhibiting projection bias in this scenario.

A high percentage of physicians who currently practice in nonmetropolitan areas grew up in similar settings, suggesting that those with experience in nonmetropolitan communities are more likely to return to these geographic areas (Rabinowitz et al. 1999). An individual calls upon their memories in predicting their future utility from an experience that has not yet occurred (Gilbert and Wilson 2007), and therefore it is likely individuals consider their previous experiences in nonmetropolitan areas when making program participation decisions. Participants with experience living in a nonmetropolitan area are likely to have a greater understanding of their taste for living in these areas, and are therefore less likely to have biased predictions of preference for living there in the future. However, the relationship between hometown population and the likelihood of completing the service obligation is insignificant in every model specification. The SLP

model does indicate that participants who grew up in a micropolitan or metropolitan community are more likely to default on their service obligations, which supports H3, yet the LRP model suggests the opposite. Furthermore, the aggregated models indicate that those who grew up in a micropolitan city are more likely to default while those with a metropolitan background are less likely to default. The small proportion of participants with metropolitan or micropolitan backgrounds could contribute to the insignificance and conflicting direction of hometown population variables, as only 10 percent and 13 percent of program participants in the analysis are of a metropolitan and micropolitan backgrounds, respectively.

The AIV appears to have no influence on the probability of defaulting or completing a program outcome. This is the case with and without including SLP participants who received the low-interest loan. While greater incentive values may entice more individuals to participate in healthcare financial incentive programs, it appears that the value of the incentive does not influence one's likelihood of completing or defaulting on their obligation. Thus, the impact of varying incentive values does not appear to influence the propensity of exhibiting projection bias. The consistent insignificance of this variable is an interesting result, as it suggests that the value of incentives healthcare professionals receive doesn't influence the likelihood that one will be recruited and fulfill a service obligation in a shortage area. In combination with weak evidence that default conditions deter default outcomes, it appears that individuals are influenced by factors beyond financial considerations of their service contract in making default or fulfillment decisions, and that financial incentives or penalties may not be adequate in prompting individuals to accurately predict future preferences.

6.2.2 Other Considerations

LOT is a consistent variable across models involving SLP participants, leading to the conclusion that LOT leads to greater likelihood of defaulting on service-obligations within student-targeted programs. This is certainly influenced by physicians, who have the longest training of all professionals in the data. While physicians could be more likely to default if salaries in non-shortage areas were markedly higher than those in shortage areas, evidence on physician salaries suggests that this is not the case. The Center for Studying Health Systems Change (2005) reports the difference between metro and non-metro physician income is negligible. Furthermore, after adjusting for cost of living in metro and non-metro areas, adjusted physician income is actually greater in non-metro areas. Because of this, and lack of usable, spatially explicit data on incomes across professions, income earnings between metro and non-metro areas were not utilized in the regression.

6.2.3 Survival Analysis

Because this analysis excludes all participants who defaulted on their service obligation prior to or shortly after entering a shortage area, it excludes those subjects who exhibited initial signs of projection bias. By defaulting before beginning practice in a shortage area, individuals demonstrated their imperfection at predicting what future preferences would result in the greatest level of utility. Thus, by only including those who have completed their service obligation, subjects in this analysis inherently have a lower propensity of exhibiting projection bias in terms of their practice specialty and shortage area location, as all spent the time required in their shortage area. However, recall that equation 3 describes that individuals will complete their practice obligation if the

difference in utility between their ideal practice location in state s and utility in the shortage area location is less than the cost of default. Thus, even if participants complete their practice obligation, projection bias-related forces may lead some practitioners to systematically leave shortage areas earlier than others in pursuit of a practice location that provides greater utility than their shortage area location. While the coefficients used in this analysis are the same as in the probit analysis, I am cautious to suggest that these are strong indicators of projection bias, rather than predictors of how soon one is likely to exit their initial shortage area location.

This analysis found that the only variable that decreases the hazard of exiting the initial shortage area is LOT, and the longer individuals spend in training results in a lower hazard of participants exiting their initial shortage area. For example, a physician is predicted to remain in their initial location longer than a physician assistant. This could be influenced by the fact that those at the peak of their profession may have an opportunity to own or buy-into their own healthcare practice. Ownership of practice is a determinant of retention used in previous studies, and Pathman et al. (2004b) reports that retention among incentive program participants is longer for those who owned their practice.

The significance of the time period variables indicate that there are unobserved forces influencing the hazard of exiting the shortage area during these time periods. I anticipate that common determinants of retention that are not included in this analysis, such as one's satisfaction in the healthcare system, work-life balance factors, and familial satisfaction in the community could be picked up in these variables. The interaction between SLP and TP3 could also reflect these factors.

Results indicate that those with a metropolitan background will spend less time in the initial shortage area compared to those with a nonmetro upbringing. Although previous studies indicate that one's background is not related to how long they remain practicing in their initial shortage area, this results supports the hypothesis (H3) that those drawing upon experiences of living in a nonmetro area are less likely to have biased predictions of the utility they will experience by living and working in similar areas.

6.3 Reducing Projection Bias in Healthcare Financial Incentive Programs

Incorrectly predicting how preferences will change over time decreases the quality of decisions individuals make for themselves. Incorrectly predicting preferences regarding practice location can have significant financial consequences both for the individual and state and federal incentive program, making it increasingly important to understand how the magnitude of projection bias can be reduced.

Initial predictions of future preferences require time, motivation, and cognitive resources. When any of these are lacking, adjusting preferences are inaccurate and biases will occur. Ubel, Loewenstein, and Jepson (2005) found that prompting individuals to think more carefully about the process of adaptation could reduce projection bias. While I expected that semi-annual letters and changes to the cost of default would induce individuals to think more carefully about their preferences over time, results do not strongly support default condition changes resulted in higher completion rates. Thus, it is possible that a more explicit prompt, perhaps an exercise before or during the incentive program application process, could help guide individuals to consider their experience in professional school and how these experiences may influence their practice preferences in the future. Furthermore, because a major cause of projection bias in healthcare

financial incentive programs is caused by the temporal gap between when an incentive is received and service obligation is carried out, prompting individuals to mentally simulate what it is like to live and work in a shortage area and then correct for its temporal location could help to overcome some bias (Gilbert, Gill and Wilson 2002). Such correction could involve prompting individuals to consider features outside of medicine that they may not otherwise consider, or prompting students to consider how their state between the current time period and future will change.

If individuals do not invest adequate cognitive resources in assessing their future preferences, it will cause their predictions to be overly influenced by current feelings rather than by their knowledge of the event's temporal location (Gilbert, Gill, and Wilson 2002). Thus, giving decisions adequate time to think about the utility these decisions will provide when experienced across a variety of scenarios, temporal locations, or states is important in reducing the magnitude of projection bias.

Programs may also consider limiting who is eligible for programs based on the length of training remaining. It appears that student-targeted programs are best designed for professionals with shorter training periods, which would shorten the temporal gap between the time of deciding to participate and the time the service obligation is carried out. If student-targeted programs were specifically designed for mid-level healthcare professionals or if those with longer training periods received a financial incentive later on in training—e.g., the end of school or beginning of residency—it could decrease the magnitude of projection bias and improve outcomes of student-targeted programs.

Projection bias could also be reduced and program outcomes improved if the financial incentive in the SLP were made salient at the time the program obligation is

being fulfilled. One strategy to do so would be to wait to award a small portion of the financial incentive once providers are practicing in a shortage area.

Continuing the practice of providing incentives to those with demonstrated experience of living in nonmetro, underserved areas is important in mitigating the strength of projection bias. It could also reduce bias and improve completion rates to require that all participants experience a rotation in a shortage area location prior to committing to an incentive program.

6.4 Limitations

The HPTS repository only tracks healthcare providers in Nebraska and western Iowa. Thus, there is potential for bias due to missing data of those who left the State of Nebraska and are no longer tracked through the HPTS. Additionally, a portion of the HPTS is self-reported through provider surveys and relies solely on the response of healthcare providers. Variables such as high school graduation city, for instance, are missing from a portion of observations due to nonresponse and are excluded from the analysis.

The timeline of the data collection and tracking of healthcare providers is a limitation to this research. The first incentive program began in 1979, but HPTS tracking didn't start until 1995. While this primarily affects participants of the SLP, there is likely missing data of location and duration of practice prior to 1995. The research controls for this discrepancy by identifying providers whose first practice location in the HPTS matches the service-obligation practice location reported by the Nebraska Department of Health and Human Services to ensure data accuracy. This limitation only influences the survival analysis regression, and is unlikely to affect the probit model regression, as it

simply looks at the program outcome, and does not consider practice locations immediately after training.

The cox hazard regression analysis does not take into account the subsequent practice location. It is possible that even when individuals exit their initial shortage area, they relocate to a different shortage area location. This analysis also does not account for common determinants of retention such as workplace and community satisfaction, practice and community attributes, or additional personal characteristics.

CHAPTER 7: SUMMARY AND CONCLUSIONS

Financial incentive programs are likely to become increasingly attractive to young professionals. As the debt burden of students increases, so does the propensity to enroll in a financial incentive program (Jackson et al. 2003). In order to influence the impact that financial incentive programs have in addressing geographic healthcare disparities, it is vital to analyze what program design features and participant characteristics are most likely to result in completed program outcomes. Understanding the psychological forces that are influenced by these features makes studying behavioral economic concepts such as projection bias relevant in designing programs to alleviate underserved healthcare populations.

This analysis addresses which elements of program design in student-targeted and professional-targeted programs are likely to be influenced by projection bias, and if these elements are expected to counteract or contribute to its prevalence. If design elements of certain programs give way to the likelihood of projection bias, then the efficacy of these programs may be hindered. Overall, this analysis supports that participants of student-targeted programs are significantly more likely to exhibit projection bias, and therefore default on service obligations. Furthermore, the longer students are in training, the more likely they are to make biased predictions about their future practice preferences within student-targeted programs such as the SLP. These results are likely caused by the temporal gap between when the commitment to practice in a shortage area is made and when the service obligation is carried out. The greater the time between these points results in higher magnitudes of projection bias, and therefore higher likelihood of defaulting on one's service obligation. Although those who had longer training periods

were more likely to exhibit projection bias in terms of fulfilling their practice obligation, of those who did complete their obligation, participants with greater training periods had a lower hazard of exiting their initial shortage location.

The extension of projection bias theory proposed in this thesis, along with previous studies, suggest there is potential to decrease the magnitude of projection bias by increasing the perception of how bound one is to fulfilling their obligation. While the results of this research do not strongly support this claim, additional research could provide insight into what features are likely to make participants feel more bound to their obligation. High default costs do not appear to have a strong impact on biased predictions or program completion rates. Conducting experiments to explore why financial penalties do not correct behavior and what type of prompts would induce greater cognitive effort in predicting future preferences, leading to de-biased decisions, could provide insight into this observation.

By addressing the causes of projection bias and strategies to decrease its prevalence, it is possible to improve program outcomes for student-targeted programs. By inducing students to think more carefully about how their specialty and practice location preferences may change over time, and the new experiences they will encounter throughout the course of their training, individuals may decrease their bias by placing less weight on their current preferences. Furthermore, providing student-targeted incentives to mid-level healthcare providers could improve the outcomes of these programs because they have shorter training periods.

Despite the many efforts and interventions that have been implemented by medical schools, the federal and state governments, and healthcare systems,

nonmetropolitan healthcare disparities persist, requiring that additional research, innovation, and collaboration are needed among stakeholders to achieve long-term solutions to this issue.

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