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Essays on Risky Health Behavior

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ESSAYS ON RISKY HEALTH BEHAVIORS

BY

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DISSERTATION

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Dedication Page

This is dedicated to the three individuals who have had the greatest influence on my academic achievement. First, I dedicate this to Glen Dealy the Elder, who convinced me to go back to school when I was a 22 year old meat cutter without a high school diploma or GED. I do not think this is exactly what you meant at the time, but your words set all of this in motion. Next, I dedicate this to Glen Dealy the Junior, who arrived shortly after my PhD journey began. I have not had a bad day since you were born. Finally, I dedicate this to my wonderful wife Genevieve. I will always be grateful for the sacrifices you made so that I could follow a dream. Before we came to New Mexico, we made a deal that after I finished graduate school, you would go. Later on, you expressed some doubt and I told you that if you did not go, I would go back and get a law degree. It may have seemed like a joke at the time, but I assure you it was not. And now it is in writing.

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ABSTRACT

Risky health behaviors including substance abuse and risky sex are a significant contributor to chronic illness in the US. Efficient use of public resources to avert or mitigate the consequences of risky health behaviors requires a better understanding of the overall costs of risky health behavior to society. Additionally, a better understanding of the value and behavioral consequences of programs designed to mitigate the consequences of risky health behavior is needed. This dissertation utilizes a number of unique methodological and empirical tools to examine the consequences of risky sex and drug abuse and the value of policies which seek to avert or mitigate the impact of the consequences.

The first study uses a spatial difference-in-difference identification strategy to estimate the impact of clandestine drug lab discovery and decontamination on proximal home values. Results suggest that the discovery of a lab causes nearby home prices to

drop significantly, while the decontamination of a lab causes nearby home prices to increase significantly, partially offsetting the impact of discovery.

The second and third studies investigate the impacts of behavioral interventions designed to reduce risky sexual behavior, including market and nonmarket costs. Overall the results show that risky-sex behavioral interventions can generate substantial cost-savings. Furthermore, the results show that interventions may affect the willingness to pay to avoid the consequences of risky sexual behavior.

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Chapter 1: Introduction

1.1 Risky Health Behaviors

Economic research of risky health behaviors has grown considerably in recent years. Although prior to 1980, there were relatively few economic studies of risky health behaviors, research has expanded considerably in the last few decades, both in terms of theoretical and applied contributions (Cawley & Ruhm, 2011). Any deliberate action or inaction which can potentially yield negative health consequences could be considered a risky health behavior. However, the types of risky behaviors that are examined in this dissertation are those which can also be characterized by a disconnect between gratification and consequence. In spite of this disconnect, a number of studies have found evidence that in the context of risky health behaviors, incentives still matter. For example, Klick and Stratmann (2007) find that laws requiring parental consent for teens to obtain abortions (thereby increasing the cost of risky sexual behavior) reduces risky sexual activity. Similarly, Klick and Stratmann (2003) find that when access to abortion increases (thereby decreasing the cost of risky sexual behavior) risky sexual activity increased.

Given that incentives matter in the context of risky health behaviors, individual preferences are also thought to contribute to risky health behaviors. The bulk of the work in this area is focused on heterogeneity in time preferences, as well as the specification of the proper discount function to explain risky health behaviors. For example, previous

work has found that in numerous risky health behavior contexts, individuals' exhibit time preferences consistent with a hyperbolic discount function (Loewenstein & Prelec, 1992), suggesting that individuals preferences may not be time consistent.

A very important and understudied aspect of risky health behavior is information. Decisions in this context can impose irreversible and severe consequences. Furthermore, in the context of risky health behaviors, information can be rather complicated, as it requires not only an awareness of the potential consequences associated with a behavior, but also an understanding of how the behavior affects the likelihood of experiencing the consequences. Awareness of consequences has been found to be an important determinant of risky health behaviors (Lee, Chen, Liu, Hung, & Huang, 2010). Further complicating matters is the role of addiction which is associated with a number of risky health behaviors. For example, even if an individual is aware of the consequences of smoking, and has an approximate understanding of how the choice to initiate smoking today may affect future health outcomes, they may not understand their body's physiological response to the addictive substance. Even when individuals understand the full extent of the consequences, they can overestimate their ability to overcome addiction (Slovic, 2000, 2001). Thus, public policies which only address information are often only partially effective (Loewenstein, Brennan, & Volpp, 2007).

Another contributing factor to the disconnect between gratification and consequence of risky health behaviors is the existence of externalities. The individuals who choose to engage in these behaviors often do not bear the full cost of their activities. For example, cigarette smokers expose others to environmental tobacco smoke and fire hazards (Chaloupka & Warner, 2000; Sloan, 2004). The external costs generated by

excessive drinking include the costs experienced by victims of drunk driving accidents and public expenditures associated with prosecution and incarceration of drunk drivers (Greenfield et al., 2009; Levitt & Porter, 2001).

Public policy motivates much of the economic research of risky health behaviors. Risky health behaviors have a large impact on morbidity and mortality in the US. Over one-third of all deaths in the US can be attributed to modifiable behaviors such as smoking, alcohol abuse, poor diet and risky sexual behavior (Schroeder, 2007). The treatment of chronic illness attributable to risky health behaviors account for over 75% of all health care costs (Fisher et al., 2011), and a significant portion of these treatment costs are paid for with public spending. The externalities associated with risky health behaviors also motivate a number of policy questions.

Well-informed policy in this context requires an understanding of all the consequences associated with these behaviors and all of the impacts associated with alternative policy options. This dissertation utilizes a number of unique methodological and empirical tools in order to examine the consequences of risky sex and drug abuse and the value of policies which seek to avert or mitigate the impact of these consequences. The study presented in Chapter 2 is a revealed preference hedonic home price study which investigates a consequence of drug abuse that has received little attention: the impact of clandestine drug lab discovery and decontamination on proximal home values. A stated preference contingent valuation study is conducted in Chapters 3 to examine the nonmarket value of avoiding sexually transmitted infections, a consequence of risky sexual behavior. The study presented in Chapter 4 also examines sexually transmitted infections, but considers these costs from a societal perspective. Specifically, the study

presented in Chapter 4 evaluates two distinct risky-sex behavioral interventions. Although Chapters 2 and 3 focus on nonmarket values, the focus of Chapter 4 is explicitly on market costs. This study illustrates the use of a Bernoulli probability model linking observed changes in behavior to expected changes health outcomes, which are monetized using treatment costs.

1.2 Methamphetamine Abuse, Risky Sex and Policy

Substance abuse in the US imposes a substantial economic burden in the US. The estimated cost of illegal drugs exceeds $226 billion per year (Kasunic & Lee, 2014). Recently, the rate of methamphetamine (meth) abuse in the US has been increasing (Gruenewald et al., 2013). It is widely known that meth users suffer devastating health effects. However, the impacts of meth are not limited to private costs experienced by the user. In particular, meth users engage in more violent behaviors (Dawe, Davis, Lapworth, & McKetin, 2009), and empirical evidence suggests that meth abuse can lead to increased rates of child neglect and abuse (Cunningham & Finlay, 2013). Additionally, clandestine meth labs have been known to cause adverse health effects for not only the drug manufacturers, but also law enforcement officers, fire personnel, and residents living near the clandestine labs (Ross & Sternquist, 2012). Meth labs also pose an environmental health risk, as one pound of meth yields five to six pounds of hazardous waste which is often dumped in the surrounding neighborhood (Joint Federal Task Force of the Drug Enforcement Administration, U.S. Environmental Protection Agency, & U.S. Coast Guard, 2005).

Policy interventions which address meth labs have focused on prevention, rather than remediation (Bobo, 2013). Recent policies, such as the Combat Methamphetamine

Epidemic Acts of 2005 have restricted producers' access to meth precursor chemicals, significantly reducing the incidence of meth lab discoveries, as well as the scale of labs in the US (Shukla, Crump, & Chrisco, 2012). However, an important issue facing policymakers is how to manage properties where meth labs have already been discovered. Numerous media outlets have reported negative effects for individuals moving into homes that were unknown to be contaminated with meth by the previous occupants. And while meth labs have surfaced in every state in the US, only half have enacted legislation which mandates lab decontamination. One of the most vocal arguments against mandatory remediation is that the cost of decontamination falls on the homeowners, which may not have had any involvement in the production of meth. Many meth labs are discovered on rental properties.

Risky sexual behavior imposes a considerable burden on the healthcare system. One-third of all Americans will contract a Sexually Transmitted Infection (STI) at some point in their lives (Summers, Kates, & Murphy, 2002) and the lifetime treatment costs resulting from a single year of STIs in the US exceeds $15.6 billion. Marginalized groups, such as justice-involved youth and men who have sex with men (MSM) are at particularly high risk for STIs, as both groups contract a disproportionately large number of new infections (CDC, 2015; H. W. Chesson, J. M. Blandford, T. L. Gift, G. Y. Tao, & K. L. Irwin, 2004). One approach to reducing STI incidence are behavioral interventions designed to reduce risky sexual behaviors. However, the implementation of these programs often requires public resources. While efficacy of a particular program is important to public health planners, they also need to understand how these programs

benefit the individuals for whom the program is implemented, as well as the social benefits.

1.3 Contributions of this Dissertation

This dissertation uses a variety of methods to evaluate the consequences of risky health behaviors. Chapter 2 uses the hedonic home price method to investigate externalities associated with meth production in residential neighborhoods. The study presented in Chapter 3 uses a contingent valuation survey to estimate the nonmarket value of STI avoidance as well as the impact of a behavioral intervention on willingness to pay. The study presented in Chapter 4 also examines the consequences of risky sexual behavior. However, the study presented in Chapter 4 utilizes a deterministic model which links changes in behavior to changes in expected health outcomes in order to monetize the impacts of behavioral interventions designed to reduce risky sexual behavior.

The analysis presented in Chapter 2 examines how meth labs located in residential neighborhoods affect the property values of nearby homes. This study uses a novel dataset constructed from geo-coded meth lab and property sale data in Linn County, Oregon. To determine the impact of clandestine meth lab discovery and decontamination on proximal home values, a hedonic home price study is conducted using a quasi-experimental, difference-in-difference, spatial identification strategy. This is the first study to consider the positive impacts of meth lab decontamination alongside the negative impacts of meth lab discovery. Thus, the findings presented in Chapter 2 could provide insight into the value of policies related to both prevention and mitigation of clandestine drug labs.

The study presented in Chapter 3 examines the nonmarket value of STI avoidance using a contingent valuation survey. The contingent valuation survey data presented in Chapter 3 were obtained during the clinical trial of a risky sex behavioral intervention designed for justice-involved youth. Although the use of contingent valuation in health economics has expanded considerably in recent years, there is, relatively, a dearth of work applying contingent valuation in the context of STIs. Furthermore, while a handful of studies have utilized contingent valuation methods in the context of STIs, this is the first to investigate how a risky-sex behavioral intervention may affect the willingness-to-pay to avoid the consequences associated with risky sexual behavior. Specifically, willingness to pay is elicited before and after the behavioral intervention, which allows for the impact of the intervention on the perceived value of STI avoidance to be tested.

Chapter 4 presents another study of the consequences of risky sexual behavior. However, the focus of Chapter 4 is on quantifying the impacts of two distinct behavioral interventions designed to reduce risky-sex behaviors. The efficacy of both of these behavioral interventions have been verified in previous work (Kurtz, Stall, Buttram, Surratt, & Chen, 2013). However, while clinical efficacy in this context is based on how the intervention affects behavior, the economic impacts are determined by health outcomes. As health outcomes were not observed during the clinical trials for these behavioral interventions, behavioral data, collected at multiple nodes during the clinical trials of these interventions is used to predict changes in health outcomes. The data used in Chapter 4 were obtained during the clinical trial of two distinct risky-sex behavioral interventions designed specifically for substance-using men who have sex with men. Chapter 4 illustrates the use of a Bernoulli probability model to translate changes in risky

sexual behaviors attributable to a behavioral intervention, into changes in health outcomes. This study is unique in the level of detail regarding risky sexual behavior. In particular, while the Bernoulli model used in this study is based on previous work, it is adapted in order to incorporate the risks associated with numerous sexual acts, which correspond to widely varying levels of STI transmission rates and prevalence.

Chapter 2: The Impact of Clandestine Methamphetamine Lab Discovery and Decontamination on Property Values

2.1 Introduction

Substance abuse imposes a substantial economic burden in the United States (US), where it is estimated that the cost of illegal drug abuse exceeds $226 billion per year (Kasunic & Lee, 2014). While a number of studies have investigated the economic burden of substance use disorders, there is still a number of aspects about these social costs that are not well-understood. For instance, it is common for economic studies of substance use disorders to focus on three outcome domains (increased health care costs, crime and lost productivity), when the true cost of substance use extends to a number of areas that are still relatively unexplored. Notably, there are relatively few examples of previous work evaluating the impact of illicit drug production on property values. This study evaluates the impact of illicit drug production on property values in a particularity relevant domain: the impact of clandestine methamphetamine (meth) labs on proximal residential property values.

For background on methamphetamine (meth), it is a particularly devastating and cheap drug, with a relatively long half-life (Shoptaw & Reback, 2007), and use in the US has increased substantially in recent years (Gruenewald et al., 2013). While causality is actively debated (Mialon, Nesson, & Samuel, 2014), individuals under the influence of meth commonly engage in higher rates of risky sexual behavior (Purcell et al., 2005) and

violent behavior (Dawe et al., 2009). Also, meth use has been found to be associated with child neglect, child abuse, and an increased burden on the foster care system (Cunningham & Finlay, 2013).

It is estimated that in the US, the annual societal burden of meth is nearly $23.4 billion (Nicosia, Pacula, Kilmer, Lundberg, & Chiesa, 2009). Beyond the standard cost estimates, clandestine meth laboratories (labs) are often located in residential neighborhoods, and can pose health risks and potential damage to the personal property of individuals living in nearby homes. Recent policies at both the state and the federal level have helped to curb the incidence of domestic residential meth production.[1] But, supplemented by foreign production, the meth supply chain has continued to meet demand and domestic meth consumption continues to be a substantial problem.

An important issue facing policy makers is how to manage properties where meth labs have already been discovered. Meth becomes airborne during the cooking process, and contaminates the surfaces of homes (counters, walls, carpets, air ducts, etc.). Additionally, meth production poses an environmental risk. One pound of meth yields five to six pounds of hazardous waste, which is often dumped in the surrounding area (Joint Federal Task Force of the Drug Enforcement Administration et al., 2005). Between 2004 and 2012, over 118,000 clandestine meth labs were discovered in the US, and while

[1] At the federal level, the Combat Methamphetamine Epidemic Act (CMEA) of 2005 considerably restricted access to methamphetamine precursors (see, e.g., Combat Methamphetamine Epidemic Act of 2005, Pub. L. No. 109-177, §§ 701-756, 120 Stat. 256 (2006)). Prior to, and following the passage of the CMEA individual states have enacted more stringent controls on meth precursors. In 2006, Oregon adopted legislation requiring individuals to obtain a prescription in order to purchase medications which contain meth precursors (P. R. Freeman & Talbert, 2012).

labs have been discovered in every state in the US, less than half have adopted legislation requiring decontamination (Bobo, 2013).

To help expand our understanding of the full impacts of drug abuse, the objective of this study is to explore the impact of illicit drug production on property values. Specifically, we evaluate the impact of clandestine meth labs on proximal residential property values in Linn County, Oregon. This county is an ideal location for this study because of its unique combination of high quality data on both meth labs and property values and its historical high incidence of meth-related events. Empirically, the impact of meth lab discovery and meth lab decontamination on nearby home prices is investigated using a quasi-experimental, difference-in-difference, spatial identification strategy, which mitigates the natural endogeneity that occurs when empirically investigating the relationship between crime and property values (Congdon-Hohman, 2013; Linden & Rockoff, 2008; Pope, 2008). Results suggest that when a meth lab is discovered, it 'Breaks Bad' for the entire neighborhood, even when accounting for the fact that meth labs are generally located in less-desirable neighborhoods with lower home prices. Additionally, although home prices recover following the decontamination of the meth lab, the recovery does not entirely offset the impact of discovery.

The next section provides background on clandestine meth labs and the policies used to decrease the incidence; Section 2.3 discusses the empirical approach; Section 2.4 describes the study area and data; Section 2.5 presents the results, including numerous auxiliary models included to test for the robustness of the empirical results; and, finally, Section 2.6 discusses and concludes the study.

2.2 Clandestine Methamphetamine Laboratories

Numerous state and federal government policies have been put in place to disrupt the supply of meth. Many of these policies have involved placing restrictions upon access to precursor chemicals used to produce meth (e.g., ephedrine and pseudoephedrine). Unfortunately, meth can be produced using numerous processes and various precursor chemicals. As a result, the meth supply chain has been able to recover quickly from these shocks. Moreover, in the notable instances where policies have been able to significantly disrupt the supply of meth (in terms of both price and purity), the market has been able to adapt and recover quickly (Dobkin & Nicosia, 2009). Additionally, as domestic meth producers are increasingly subject to the stringent regulations on precursor chemicals, larger quantities of meth are being imported from Mexico (Brouwer et al., 2006). Recently, perhaps due to increased regulation, domestic meth labs have become smaller and more urban, which has caused them to potentially be more dangerous.

While the low-probability threats associated with meth production (e.g., chemical fires, explosions, and the release of toxic gasses) are commonly known, less well-known are the systemic negative health impacts and environmental pollution generated by meth production. For instance, numerous media outlets have reported negative effects experienced by individuals moving into homes that were not known to be contaminated with meth by the previous occupants.[2] Moreover, meth production has been known to cause adverse health effects for drug manufacturers, law enforcement officers, fire and police personnel and residents living near laboratory sites (Nicosia et al., 2009).

[2] An interested reader should refer to (Dewan & Brown, 2009).

However, while clandestine meth labs have appeared in every state in the US, less than half of the states have recognized the need to decontaminate homes where meth has been produced.

An example of a state which has adopted mandatory cleanup legislation is State of Oregon. In 1990, the Oregon Health Authority's (OHA) Clandestine Drug Lab Program (CDLP) was created and tasked with administering the decontamination and cleanup of meth (and other clandestine drug) labs discovered in the state. When a suspected lab is reported, contractors licensed by the CDLP inspect the property for contamination. To be re-occupied, any homes found to be contaminated must submit a cleanup work plan that needs to be approved by the CDLP. Once approved, the cleanup can be performed, and only then can the site must be re-inspected and issued a certificate of fitness from the CDLP.[3] All State and Local agencies that suspect a property has been used in the illicit manufacture of drugs must be reported to the CDLP and undergo an inspection. Furthermore, homeowners are legally required to report their property for inspection if there are "reasonable grounds to believe that the property has been used as an illegal drug manufacturing site" ("Or. Rev. Stat. Ann. § 453.861," 1989).

2.3 Theoretical Approach

Hedonic home price studies use observations of behavior within the housing market in order to infer consumers' willingness-to-pay for a non-market amenity (or

[3] More detail on lab cleanup procedures can be obtained from Oregon Department of Human Services (2015).

disamenity). The theoretical basis for hedonic valuation is based on the work of Rosen (1974), who outlined a model of consumer behavior to describe the market for differentiated goods. The basic theory of hedonic markets assumes that consumers derive utility from the consumption of a specific heterogeneous good represented by a vector Z of characteristics, along with a composite good Y priced at unity. Household preferences are represented by the utility function

$$u = u(Y, Z) \tag{2.1}$$

The budget constraint, M is constant in any period and is represented as

$$M = Y + P(Z) \tag{2.2}$$

where $P(Z)$ represents the hedonic price function. Utility is maximized with respect to home characteristics and consumption of the composite good.

$$\max_{Z,Y} u(Y, Z) \text{ subject to } P(Z) + Y \leq M \tag{2.3}$$

Consumption of the composite good is replaced by $Y = M - P(Z)$, which yields the first order conditions

$$\frac{u_z(M - P(Z), Z)}{u_Y(M - P(Z), Z)} = P_z(Z) \tag{2.4}$$

The slope of the hedonic price function is equal to the marginal rate of substitution between the attribute and the numeraire good. A buyer's maximum bid for a house is described by the bid function, $\beta(Z; u, M)$ which holds utility and income fixed. The bid function represents what a consumer would pay for alternative attribute vectors at given

levels of utility and income. Consumption of the composite good can be replaced by $Y = M - \beta(Z)$. Utility maximization yields the first order conditions,

$$\frac{u_z\left(M-\beta(Z),Z\right)}{u_Y\left(M-\beta(Z),Z\right)} = \beta_Z(Z) \tag{2.5}$$

The slope of the bid function are also equal to the marginal rate of substitution, which suggests that in equilibrium, the bid function is tangent to the hedonic price function. This result justifies the use of hedonic models to study consumer welfare. In equilibrium, consumers' willingness-to-pay is equal to the observed hedonic price function.

In practice, the vector of attributes which define a home Z is broken down into numerous categories of vectors, including structural (S), neighborhood (N) attributes, and spatial and temporal location in relation to meth labs, (Q). Consumers choose the utility-maximizing home from available homes, subject to their budget constraint. Assuming that the housing market is in equilibrium, the price of the ith home (P_i) will be determined by the hedonic price function,

$$P_i = P(S_i, N_i, Q_i) \tag{2.6}$$

The partial derivative of the hedonic price function with respect to the characteristic or attribute of interest is the marginal implicit price for that attribute (Freeman III, 1995).

Hedonic price theory has been used to estimate a number of nonmarket housing attributes. Historically, hedonic home price studies have focused on environmental amenities and dis-amenities, including air quality (Graves, Murdoch, Thayer, & Waldman, 1988), proximity to landfills (Hite, Chern, Hitzhusen, & Randall, 2001), and noise (McMillan, Reid, & Gillen, 1980). A number of studies have considered dis-

amenities which are accompanied by uncertain health effects. Davis (2004) considered the effect of cancer clusters on home prices, finding that a sudden spike in pediatric leukemia can have a significant negative impact on nearby home prices. Gamper-Rabindran and Timmins (2013) estimated the impact of Superfund remediation on home prices, finding highly localized, but significant positive impact of remediation on home prices.

Another research avenue is the impact of crime on home prices. Linden and Rockoff (2008), as well as Pope (2008) considered the impact of sex offender proximity on home prices. Both studies find significant negative impacts on home prices after a sex offender moves into the neighborhood. Pope (2008) incorporated a treatment-reversal into his estimates, and found that when the offender moved out of the neighborhood, home prices recovered significantly. Troy and Grove (2008) consider the relationship between what is generally regarded a positive neighborhood attribute (parks) and crime. Troy and Grove (2008) find that parks have a positive impact on home prices until crime rates exceed a certain threshold, at which time the park becomes more of a nuisance. Tita, Petras, and Greenbaum (2006) examine the more general impact of neighborhood crime rates, finding heterogeneous impacts based on neighborhood affluence and the rates of specific crimes. Beyond studies of home prices, hedonic price theory is used to estimate characteristics of a variety of differentiated goods, including tomatoes (Jordan, Shewfelt, Prussia, & Hurst, 1985), cotton fiber (Ethridge, 1992), hotel rooms (Tung, Lai, & Huang, 2012), rice (Goodwin, Holcomb, & Rister, 1996), and hay (Rudstrom, 2004).

2.4 Empirical Approach

2.4.1 Identification Strategy

Although the theoretical basis of the hedonic method is relatively straight-forward, estimation of the hedonic price function can often be challenging due to concerns regarding omitted variable bias. A concern relevant to the current study is meth producers' choices regarding lab location, which could be correlated with unobserved neighborhood qualities that are also correlated with price. Furthermore, controlling for initial differences between neighborhoods is insufficient if unobserved factors affecting meth producers' location choices are also a determinate of existing trends in house prices. In order to mitigate the effect of potential cross-sectional and time-series endogeneity, this study adopts a quasi-experimental strategy to identify the hedonic price function (Black, 1999; Chay & Greenstone, 1998; Linden & Rockoff, 2008).

The potential selection bias introduced by non-random meth lab location patterns is controlled for using a spatial difference-in-difference model where the treatment and control group assignment is determined by proximity to the lab. Specifically, consistent with previous studies, homes located within 0.1 miles of a meth lab are assigned to the treatment group, while homes between 0.1 and 0.3 miles from the lab are assigned to the control group (the specific choice of distance for the control and the treatment group is evaluated in the robustness section). The idea behind this identification strategy is that while meth house location choices may be endogenous and related to unobserved neighborhood factors, these omitted variables are correlated with proximity. Thus, a quasi-control group can be constructed using houses that are in close proximity to houses

affected by the meth lab. A visual depiction of the identification strategy is provided in Figure 2-1.

2.4.2 Pre-Discovery Difference Model

First, before we test the impact of meth labs on property values, the endogenous nature of meth house locations is tested by estimating whether home prices in neighborhoods where labs are *eventually* discovered differ from the prices in neighborhoods where meth labs are not discovered. This relationship is tested by estimating a pre-discovery difference model, where homes in the treatment and control group (i.e., homes within 0.3 miles of a lab) are excluded from the estimation if the sale took place after the discovery of the lab. This model is specified as follows:

$$\ln\left(P_{ijt}\right) = \beta X_i + \left(\theta_1 D_{ijt}^{0.1} + \theta_2 D_{ijt}^{0.3}\right) + \gamma_j + \lambda_t + \varepsilon_{ijt} \qquad (2.7)$$

where $\ln\left(P_{ijt}\right)$ is the natural log of house i's inflation-adjusted sale price, and the vector X_i includes the structural $\left(S_i\right)$ and neighborhood $\left(N_i\right)$ characteristics specific to the house. The subscripts i, j and t refer to individual, census block and time components of the model respectively. The homes in the treatment group are indicated by the binary variable $D_{ijt}^{0.1}$, which is equal to one if the home is within 0.1 miles of where a lab will *eventually* be discovered, (otherwise zero). The binary variable, $D_{ijt}^{0.3}$ indicates membership in the control group, where $D_{ijt}^{0.3}$ is equal to one if the home is located within 0.3 miles from where a lab will *eventually* be discovered, otherwise zero. Finally, ε_{ijt} is a

random error term, (including census-block and time fixed effects) and α, β, θ_1 and θ_2 are parameters to be estimated.

In this initial specification, because homes within 0.3 miles of a lab are excluded if they were sold after the lab was discovered, this model estimates the preexisting difference in home prices for the neighborhoods where meth labs do eventually locate. If meth labs locate entirely at random (i.e., no endogenous location choices), then the estimated coefficient on the binary control group variable would be equal to zero $(H1_0 : \theta_2 = 0)$. Alternatively, if the location of meth labs is not random, and is actually influenced by pre-existing differences in property values, the estimated coefficient on the binary control group variable would not be equal to zero $(H1_a : \theta_2 \neq 0)$. Additionally, if there are not pre-existing differences between homes within 0.1 miles and homes between 0.1 and 0.3 miles of a meth house, the estimated coefficient on the binary treatment group variable would be equal to zero $(H2_0 : \theta_1 = 0)$. Otherwise, if these areas are not comparable we would find that the estimated coefficient on the binary treatment group variable would not be equal to zero $(H2_a : \theta_1 \neq 0)$. Overall, it is expected that $\theta_2 \neq 0$ and that $\theta_1 = 0$, indicating that meth labs generally locate in neighborhoods with lower property values, but that there are no pre-existing differences between the prices of our treatment and control groups.

2.4.3 Lab-Discovery Difference-in-Difference Model

Because we expect to find that meth producers do in fact choose lab locations based on unobservable factors correlated with proximity, the following difference-in-difference model is specified to estimate the actual impact of lab discovery:

$$\ln\left(P_{ijt}\right) = \beta X_i + \left(\theta_1 D_{ijt}^{0.1} + \theta_2 D_{ijt}^{0.3}\right) + \left(\theta_3 D_{ijt}^{0.1} + \theta_4 D_{ijt}^{0.3}\right)\tau_{it}^{\text{disc}} + \gamma_j + \lambda_t + \varepsilon_{ijt} \qquad (2.8)$$

This specification is similar to Eq. 2.2, except the full dataset is used and a binary variable τ_{it}^{disc} is included, which is equal to one if the property sale occurs after the lab is discovered, otherwise zero. Thus, in this difference-in-difference specification, the coefficients θ_1 and θ_2 will capture pre-existing home price differences in the treatment and control groups, and θ_4 will capture time trends associated with being in an area where meth houses locate, allowing θ_3 to capture the impact of lab discovery on proximal home prices. If the differences in home prices around meth labs are due solely to pre-existing differences in home prices, the lab discovery should have no impact on home prices $\left(H3_0 : \theta_3 = 0\right)$. Alternatively, if the discovery of the lab does affect the prices of homes in surrounding areas, then the estimated coefficient on the interaction between the binary distance variables and the timing variables would not be equal to zero $\left(H3_a : \theta_3 \neq 0\right)$.

2.4.4 Lab Discovery and Lab-Decontamination Difference-in-Difference Model

In addition to allowing for the estimation of the impact of meth lab discovery, a novel feature of the OHA CDLP dataset is that it contains information on the timing of

meth lab decontamination. This information is included in the empirical model, using the following difference-in-difference model

$$\ln\left(P_{ijt}\right) = \beta X_i + \left(\theta_1 D_{ijt}^{0.1} + \theta_2 D_{ijt}^{0.3}\right) + \left(\theta_3 D_{ijt}^{0.1} + \theta_4 D_{ijt}^{0.3}\right)\tau_{it}^{\text{disc}} + \left(\theta_5 D_{ijt}^{0.1} + \theta_6 D_{ijt}^{0.3}\right)\tau_{it}^{\text{clean}} + \gamma_j + \lambda_t + \varepsilon_{ijt} \quad (2.9)$$

where the binary variable, τ_{it}^{clean} is equal to one if the home is sold after the discovered meth lab has been decontaminated, otherwise zero. If lab decontamination did not have an impact on home prices the estimated coefficient on the interaction between the binary treatment group variable and lab decontamination timing variable would be equal to zero $\left(H4_0 : \theta_5 = 0\right)$. Alternatively, if the decontamination of the lab has an impact on the sale price of the home, then this would not be equal to zero $\left(H4_a : \theta_5 \neq 0\right)$.

2.4.5 Auxiliary Models

A number of auxiliary models are specified to determine the robustness of the primary model results. First, the binary distance variables specifications in the primary model reflect the choices of a previous study (Linden & Rockoff, 2008) examining the impact of sex-offenders moving into a neighborhood. However, Linden and Rockoff (2008) choice of 0.1 and 0.3 were justified by statute: all the households within 0.3 miles of the sex-offender's new home had to be notified when the offender moved in. There is no equivalent notification statute regarding meth labs. In order to determine whether the impact of the choice of distance for the treatment and control groups is

$$\ln\left(P_{ijt}\right)=\beta X_i+\left(\theta_1 D_{ijt}^{\text{Treatment}}+\theta_2 D_{ijt}^{\text{Control}}\right)+\left(\theta_3 D_{ijt}^{\text{Treatment}}+\theta_4 D_{ijt}^{\text{Control}}\right)\tau_{it}^{\text{disc}}+\left(\theta_5 D_{ijt}^{\text{Treatment}}+\theta_6 D_{ijt}^{\text{Control}}\right)\tau_{it}^{\text{clean}}+\gamma_j+\lambda_t+\varepsilon_{ijt} \quad (2.10)$$

where the distance cutoff for the binary variable, $D_{ijt}^{\text{Treatment}}$ varies between 0.1 and 0.2 miles, and the distance cutoff for the binary variable, D_{ijt}^{Control} varies between 0.2 and 0.5 miles.

The next auxiliary model is motivated by variable coding. In particular, the timing and distance binary variables in the primary model are overlapping. For example, if a home is within 1 tenth of a mile to a lab, $\left(D^{0.1}=1\right)$, then $\left(D^{0.3}=1\right)$. Alternatively, the variables could be coded such that they are exclusive. The econometric specification is identical, however the interpretation of the coefficients on the variables is slightly different. Similar to Eq. 2.8, a lab discovery model is specified as

$$\ln\left(P_{ijt}\right)=\beta X_i+\left(\psi_1 D_{ijt}^{0.1}+\psi_2 D_{ijt}^{0.3}\right)+\left(\psi_3 D_{ijt}^{0.1}+\psi_4 D_{ijt}^{0.3}\right)\tau_{it}^{\text{disc}}+\gamma_j+\lambda_t+\varepsilon_{ijt} \quad (2.11)$$

However, while the coefficient, θ_1 in Eq. 2.8 refers to the marginal effect of living within 0.1 miles of a meth lab, regardless of timing, the coefficient ψ_1 in Eq. 2.11 is the marginal effect of living within 0.1 miles of a lab, prior to the discovery of the lab. Similarly, ψ_2 is the marginal effect of living between 0.1 and 0.3 miles of a meth lab, prior to the discovery of the lab. The coefficients ψ_3 and ψ_4 capture the marginal effect of living within 0.1 miles or between 0.1 and 0.3 miles, after the discovery of the lab, respectively. Next, a lab decontamination model is specified similar to Eq. 2.9

$$\ln\left(P_{ijt}\right)=\beta X_i+\left(\psi_1 D_{ijt}^{0.1}+\psi_2 D_{ijt}^{0.3}\right)+\left(\psi_3 D_{ijt}^{0.1}+\psi_4 D_{ijt}^{0.3}\right)\tau_{it}^{\text{disc}}+\left(\psi_5 D_{ijt}^{0.1}+\psi_6 D_{ijt}^{0.3}\right)\tau_{it}^{\text{clean}}+\gamma_j+\lambda_t+\varepsilon_{ijt} \quad (2.12)$$

Similar to Eq. 2.11, all distance and timing variables are specified exclusively. In this specification, the coefficient ψ_3 represents the marginal effect on price for homes within 0.1 miles, after the discovery of the lab, but before decontamination. Similarly, the coefficient ψ_4 represents the marginal effect on price for homes between 0.1 and 0.3 miles, after the discovery of the lab, but before decontamination. The coefficients ψ_5 and ψ_6 represent the marginal effect on price for homes within 0.1 miles and between 0.1 and 0.3 miles, following decontamination. Similar to the primary models, the econometric models specified in Eq. 2.11 and Eq. 2.12 are estimated using the complete data set, as well as a restricted set which excludes home sales more than 0.3 miles from a lab.

The next auxiliary specification is motivated by the potential confounding relationship between time since the lab was discovered and lab decontamination. All lab decontamination takes place after the discovery of the lab. Time between discovery and decontamination can vary significantly. Thus, lab decontamination could be a proxy for time-since-discovery. To explore this possibility, the lab discovery variable is broken down into seven separate time-since-discovery variables (from 0-6 months to 36+ months in 6-month increments).

$$\begin{aligned}\ln\left(P_{ijt}\right) = {} & \beta X_i + \left(\theta_1 D_{ijt}^{0.1} + \theta_2 D_{ijt}^{0.3}\right) + \left(\theta_3 D_{ijt}^{0.1} + \theta_4 D_{ijt}^{0.3}\right)\tau_{it}^{\text{disc 0-6}} \\ & + \left(\theta_5 D_{ijt}^{0.1} + \theta_6 D_{ijt}^{0.3}\right)\tau_{it}^{\text{disc 6-12}} + \left(\theta_7 D_{ijt}^{0.1} + \theta_8 D_{ijt}^{0.3}\right)\tau_{it}^{\text{disc 12-18}} \\ & + \left(\theta_9 D_{ijt}^{0.1} + \theta_{10} D_{ijt}^{0.3}\right)\tau_{it}^{\text{disc 18-24}} + \left(\theta_{11} D_{ijt}^{0.1} + \theta_{12} D_{ijt}^{0.3}\right)\tau_{it}^{\text{disc 24-30}} \\ & + \left(\theta_{13} D_{ijt}^{0.1} + \theta_{14} D_{ijt}^{0.3}\right)\tau_{it}^{\text{disc 36+}} + \left(\theta_{15} D_{ijt}^{0.1} + \theta_{16} D_{ijt}^{0.3}\right)\tau_{it}^{\text{clean}} \\ & + \gamma_j + \lambda_t + \varepsilon_{ijt}\end{aligned} \tag{2.13}$$

The final auxiliary model is used to estimate the impact of linear distance following the discovery of the lab. Rather than a number of binary distance and timing variables, this model includes a single continuous distance variable, specified as

$$\ln\left(P_{ijt}\right) = \beta X_i + \phi D_{ijt} + \gamma_j + \lambda_t + \varepsilon_{ijt} \quad (2.14)$$

For this model, only homes within 0.3 miles of a lab which has been discovered are included. The coefficient ϕ captures the marginal effect of distance from a discovered lab.

2.5 Study Area and Data

2.5.1 Study Area

To evaluate the impact of meth houses on property values this study uses data from Linn County, Oregon. As discussed in Section 2, Oregon requires homes suspected of being used for drug manufacturing to be reported to the CDLP, which administers the decontamination process. Meth lab data was acquired through a data-sharing agreement with the OHA's CDLP, which includes the site of the lab, the date of the lab discovery, and the date the lab was decontaminated. Note that the meth lab data utilized in this study is much more comprehensive than other potential data sources that rely on the voluntary reporting of local agencies (e.g., the DEA's clandestine drug lab registry). For instance, in analysis of Linn County the full CDLP dataset includes 133 clandestine labs, whereas the DEA clandestine drug lab registry includes only 24 (Drug Enforcement Administration, 2015). Additionally, Linn County is particularly well-suited because of

the availability of high quality, detailed home sale data. While detailed property sale data is often difficult to obtain (and nearly impossible in some states, depending on the disclosure laws), the Linn County Assessor's Office makes this data easily accessible online (Linn County Assessor's Office).

Beyond the unique combination of readily available home sale and meth lab data, Linn County is also an ideal study candidate because of its geography, demographics and incidence of drug-related events. Linn County straddles Interstate-5 (which is a major route for drug trafficking in the Western US).[4] Most of the area is within an hour's drive from the urban population center of Portland, OR. Additionally, Linn County is comprised primarily of three cities with varying population levels and demographics. Figure 2-2 displays meth labs that were discovered in Linn County. The meth lab observations in Linn County are clustered around the three largest cities: Albany, Lebanon and Sweet Home. Additionally, the locations of home sales in Linn County can be seen in Figure 2-3. Similar to the locations of meth labs, home sale observations are clustered in the County's three largest cities. Note that the rural portions of Linn County (with few or no home sales) are primarily comprised of farmland and timberland. Also, previous work utilizing spatial and temporal scan statistics have found significant clustering of meth-related incidents in Linn County (Sudakin & Power, 2009).

Overall, this study utilizes property sale data collected from 1999 to 2013 and meth house data collected from 1996 to 2013. The addresses of both meth labs and property sales were geocoded using the ArcGIS database. Once the addresses were

[4] A majority of the meth labs in the CDLP data set are clustered within 20 miles of Interstate-5.

geocoded, the geodetic distance between each meth lab and each property was calculated.[5] The raw dataset contains 133 discovered labs and 29,951 property sale observations. After excluding observations with missing data, the meth lab dataset includes 99 discovered labs. After excluding observations with missing data, and limiting the property sale to residentially zoned houses and homes within Linn County's 15 incorporated cities, the property sale dataset includes 18,819 observations.

2.5.2 Data

The Linn County home sale data is quite detailed, and allow for the empirical models to control for numerous structural (S_i) and neighborhood characteristics (N_i). The structural characteristics include: the area of the housing structure $(SQUAREFT)$, specified in thousands of square feet; the number of bedrooms $(BEDROOMS)$; the number of bathrooms $(BATHS)$; the home appraisal score (between 0 and 100), $(SCORE)$; the size of the lot $(ACRES)$; age, specified as a log-transformed variable $(\ln(AGE))$; a binary variable which accounts for whether the dwelling is a manufactured home $(MANUFACTURED)$; and, a binary variable indicating whether the home is located within a quarter-mile of a school $(SCHOOL)$. Additionally, binary variables

[5] Geodetic distance is calculated as the length of the shortest curve between points along the surface of a mathematical model of the earth. Source: ArcGIS Resources (resources.arcgis.com)

were included to account for systematic differences between each of Linn County's 15 incorporated cities $(CITY)$.

The data also includes the names of the buyers and sellers, from which a number of binary variables were created. Specifically, these variables include whether the buyer purchased three or more homes during the observation period $(ACTIVEBUYER)$ and whether the seller sold three or more homes during the observation period $(ACTIVESELLER)$. These variables represent an attempt to control for buyer and seller experience in the local housing market. Additionally, binary variables indicating whether the buyer was a federal government agency $(FEDBUYER)$ and whether the seller was a federal government agency $(FEDSELLER)$. These variables are included in order to account for participation of federal government agencies in the housing market, which varied significantly during the period of observation, and peaked during the most recent recession.[6]

2.6 Results

2.6.1 Graphical Evidence

[6] When the federal government is found to be a participant in a housing transaction, the agency involved was generally the Federal National Mortgage Association ("Fannie Mae").

Figure 2-4 presents the house price gradients for the treatment and control groups both before and after the meth house was discovered.[7] Note that prior to the discovery of the lab, the price of homes in the treatment and control group generally track together and following the discovery of the lab (graphically, at day 0), a clear structural change is observed. Furthermore, the drop in treatment group home prices persists even two years after the meth lab was discovered.

2.6.2 Summary Statistics

Summary statistics are presented in Table 2.1. Of the 29,951 property sale observations in the raw dataset, approximately 11,132 observations are excluded. Observations are excluded if data is missing, or if the property did not have at least one bathroom and one bedroom. Additionally, observations are excluded if the property zoning is not residential, or if the property is not located within the boundaries of one of Linn County's 15 incorporated cities. The remaining 18,819 observations include 1,806 properties which were located within 0.1 miles of a lab and 8,025 properties which were located within 0.3 miles. There are some differences between all homes and homes within 0.3 miles of discovered meth houses. Notably, homes within 0.3 miles of a meth house have smaller acreage and are older. Alternatively, is little difference between homes within 0.1 miles of a meth house and homes within 0.3 miles of a meth lab.

[7] The graph in Figure 2-4 is generated by a kernel-weighted local polynomial regression of price on days relative to discovery

2.6.3 Empirical Results

Table 2.2 presents this study's main empirical results. The first column of Table 2.2 presents the results from the pre-discovery model (specified in Eq. 2.2). Recall that this model tests for endogeneity in meth lab location patterns by limiting the sample to home sales prior to the discovery of the lab. Overall, homes located within 0.3 miles of where a meth lab will eventually be discovered sell for substantially less (-15.13%) than homes further away. This finding suggests potential endogeneity in the patterns of meth lab discoveries (consistent with rejecting $H1_0$ in favor of $H1_a$). It is also interesting to note that homes within 0.1 miles from an eventual lab discovery did not sell at an additional discount, which suggests similarity in pricing for the treatment and control groups (consistent with failure to reject $H2_0$).

Columns 2-4 present the results of the models estimated using the full sample, and are used to test the impact of both meth house discovery and meth house cleanup on property values. Specifically, column 2 is a cross-sectional difference model, which includes housing characteristics and year and census-block fixed effects (analogous to Eq. 2.2, only estimated with the full sample), column 3 is the spatial difference-in-difference model specified in Eq. 2.3, and column 4 is the spatial difference-in-difference model, including cleanup dummies (which corresponds to Eq. 2.4). Note that all three of these models additionally include the housing characteristics and census-block fixed effects.

In terms of results it is again clear that meth houses locate in areas with lower property values as the coefficient on $D^{0.3}$ is significant in each model. However, when

housing characteristics, census-block fixed effects, and timing of lab discovery are included, the magnitude of this effect diminishes (from 4.59% to 2.76%). In terms of the impact of meth houses on proximal property values, the timing of the meth house discovery and decontamination relative to the property sale has a significant impact. This result is highlighted in the model specification which accounts for the timing of both discovery and decontamination (column 4), where the discovery of a meth lab reduces home values by 6.2% and the decontamination of a discovered meth lab generates a significant 4.71% positive impact (both significant beyond the 1% level), but does not completely offset the impact of lab discovery (consistent with rejecting $H3_0$ and $H4_0$ in favor of their respective alternative hypotheses). Additionally, our results highlight the importance of including regional proximity control trends. In both column 3 and column 4, the parameter for $D^{0.3} * \tau^{disc}$ is significant and negative (approximately -2.76% for both), indicating that locations proximal to meth labs change in value at different rates than other homes.

Due to the fact that these models utilize property sale observations outside of the treatment and control group, it is worthwhile to test for potential differences in the way that the characteristics of homes outside of the treatment and control group are valued. To do this, models analogous to Eq. 2.3 and Eq. 2.4 are estimated that exclude observations more than 0.3 miles from a lab. The results from these specifications using limited data are presented in columns 5 and 6 of Table 2.2. In column 5, none of the coefficients on the binary variables accounting for distance or timing of lab discovery are statistically significant. However, when decontamination is accounted for, (column 6) the sale price of homes located within 0.1 miles decline by approximately 5.35% (significant beyond

the 1% level). Additionally, the prices of homes within the treatment group recover by approximately 3.9% following cleanup (significant at the 5% level).

Finally, column 7 of Table 2.2 presents a model similar to column, but where the standard errors are clustered at the lab area level. In this model, the standard errors are clustered based on the first lab to be discovered within 0.3 miles of the home.

2.6.4 Marginal Implicit Price of Home Attributes

The marginal implicit price for select structural attributes are provided in Table 2.3. The variable controlling for home age is log-transformed. Thus, marginal implicit price is calculated by multiplying the average home price by the coefficient on $\ln(AGE)$ and dividing by the attribute's sample average. The remaining attributes are not log-transformed, so the marginal implicit price is found by multiplying the sample average of price by the coefficient on the attribute. The column numbers correspond to the models presented in Table 2.2. Note that marginal implicit prices are not calculated for the models in column 1 or column 7 of Table 2.2. Column 1 corresponds to the pre-discovery model, which does not include any structural attributes. The model presented in column 7 of Table 2.2 is the clustered standard error model and the coefficients and sample averages are identical to column 6.

All of the coefficients on the attributes included in Table 2.3 were significant beyond the 1% level for all model specifications. Recall that the $SCORE$ variable is a measure of home quality. The marginal implicit price of $SCORE$ varies littles across

alternative specifications (between $1,266 and $1,319). Similarly, the marginal implicit price of *BATHROOMS* is relatively invariant (between $10,114 and $10,901).

Recall that the variable *SQUAREFT* is specified as 1,000s of square feet of the structure. There appears to be a slight difference in how square footage is valued in homes closest to where labs locate. When the sample is limited to homes within 0.3 miles of a past, present or future lab, the marginal implicit price is around $42,200 per 1,000 square feet. When the full sample is included, the marginal implicit price is approximately $50,300 per 1,000 square feet. Similarly, home ageing appears to affect prices differently between homes closest to the lab and those further away. The marginal implicit price for the limited sample models is approximately -$820 per year. When the full sample is included, the marginal implicit price of an additional year of home age is approximately -$1,250. The marginal implicit price for *ACRES* is lower for homes in the limited sample models than in the full sample models (~$24,000 to ~$25,600, respectively).

2.6.5 Auxiliary Models (Robustness Checks)

Although the significance of coefficients estimated in the primary empirical specifications provide evidence of the impacts of meth lab discovery and cleanup, the optimal specification of distance-rings for the assignment of the treatment and control groups is not directly known. The choice of assigning homes within 0.1 miles of a lab to the treatment group and homes within 0.3 miles to the control group follows Linden and

Rockoff (2008); however, to assess the robustness of the estimates to the specification of distance-rings, auxiliary models are estimated analogous to the model specified in Eq. 2.4, utilizing alternative distance-ring specifications for the treatment and control group.

Table 2.4 presents the results of these auxiliary models. While changing the distance bands does have a noticeable impact on a number of parameters, the most important result is that, across all specifications, the impact of lab discovery in the treatment group is negative, and highly significant (beyond 1% for all specifications). While the impact of lab cleanup on the treatment group appears to be somewhat sensitive to the choice distance bands, the coefficient is positive and significant for most of the six specifications, losing power as the treatment and control bands increase in size.

Table 2.5 presents the results of an additional auxiliary model which accounts for the passage of time following the discovery of a lab. These models are estimated to explicitly control for the passage of time following discovery of a lab. As another study found that the impact of the lab discovery diminishes over time (Congdon-Hohman, 2013), it could be argued that the lab decontamination parameter estimated in the primary models of this study is simply acting as a proxy for the passage of time. For both models in Table 2.5, the lab discovery variable is interacted with a binary time-since-discovery variable that is grouped in 6-month bins. Column 1 of Table 2.5 excludes the decontamination parameter, and the results suggest that the over time the impact of the discovery of the lab diminishes in magnitude considerably. However, when the decontamination parameter is included (column 2 of Table 2.5), the passage of time appears to have a much smaller role in the recovery of home prices. For example, six to twelve months following the discovery of the lab, the negative impact on homes in the

treatment group is approximately -10.06% (significant beyond the 1% level). Even after 36 months, the impact of the discovery remains high in magnitude (-8.79%) and significance (beyond the 1% level). Furthermore, controlling for the potentially confounding passage-of-time effect increases the magnitude of the lab decontamination impact. When the model controls for time-since-discovery decontamination has an approximate 6.18% positive impact on the price of homes in the treatment group (significant beyond the 1% level).

The auxiliary models which include recoded distance and timing binary variables (from overlapping to exclusive) are presented in Table 2.7. In the primary models, the coefficients on $D^{0.1}$ and $D^{0.1} * \tau^{disc}$ are additive. Here, the relative magnitude of the impacts is more important, as $D^{0.1}$ is the effect on price of a home being within 0.1 miles of a lab that will eventually be discovered. Column 1 of Table 2.7 depicts the lab discovery model with exclusive coding and the full dataset, corresponding to Eq. 2.11. Homes within 0.1 miles of a lab sell at a discount of approximately 3.5% prior to the discovery of the lab, and 8% following the discovery of the lab. Column 2 of Table 2.7 presents the results from the lab decontamination model with the full dataset, corresponding to the model presented in Eq. 2.12. The results from this model again highlight the importance of accounting for lab decontamination. Prior to discovery homes within 0.1 miles of a lab sell at an approximate 3.2% discount. After discovery the homes within 0.1 miles of a lab sell at a 10.4% discount (opposed to an estimated 8% discount when decontamination is not included). After decontamination, homes within 0.1 miles of a discovered lab sell at a 6.9% discount. Note that the coefficient on the decontamination parameter is negative. This is because the model does not capture the marginal effect of

decontamination. In this specification the decontamination parameter captures the marginal effect of the home being located within 0.1 miles of discovered meth lab that has been decontamination, relative to the reference level of greater than 0.3 miles from the lab.

The auxiliary model which measures the impact of lab proximity using a continuous distance variable is presented in Column 5 of Table 2.7. Recall that this specification only includes homes within 0.3 miles of a discovered meth lab. As expected the parameter is positive (statistically significant at beyond the 1% level), indicating that home values increase as they move away from a discovered meth lab.

2.7 Discussion and Conclusion

This study uses a novel dataset constructed from geo-coded meth lab and property sale data from Linn County, Oregon to explore the relationship between meth lab discovery and decontamination on home prices. The endogeneity of meth lab locations (i.e., meth labs appear to locate in lower-priced neighborhoods) is mitigated using a spatial difference-in-difference hedonic price model.

Robust evidence is found that the discovery of a meth lab has a significant, negative impact on properties within close proximity to a lab. In our preferred model it is estimated that property values decrease by 6.2% after the discovery of a meth lab. Using a number of alternative distance specifications we find that this effect is robust (estimates vary from 6.3% to 3.1% and are all significant beyond the 1% level). In terms of lab decontamination, in the preferred distance-rings specification and in most auxiliary

specifications, we find evidence demonstrating that meth lab decontamination considerably (but not fully) offsets the impact of meth house discovery on property values. This could reflect the difference between environmental and neighborhood externalities associated with the discovery of a meth lab (e.g., McCluskey & Rausser, 2003). Nonetheless, future research is necessary to better understand the impact of meth house cleanup on property values.

Overall, these results point to a relatively unexplored negative consequence of substance abuse. Illegal drug production may cause proximal home owners to suffer reduced property values. This is bad for a number of reasons namely, that their wealth has been decreased, but also this is indicative of a reduction in welfare associated with those living in this area. Additionally, there could be a loss of tax revenue from these properties.

While this study finds that lab discovery and lab decontamination has a statistically significant impact on home prices, this evidence should be interpreted carefully as this study currently has a number of limitations. First, it is possible that meth labs were observed within the neighborhood (and potential buyers) before formally documented in the OHA CDLP dataset. To assess the impact of a potential lag between the time that neighboring property owners observe the lab and the lab being reported to the OHA CDLP, an auxiliary model is estimated where property sale observations in the treatment group are excluded if they took place during the 6 months prior to OHA CDLP notification. The estimated impact of lab discovery actually increases in this specification, and remains statistically significant beyond the 1% level. Finally, while the availability of Linn County meth house and property value data made it ideal for this

study, the findings are not necessarily generalizable and future work should explore other states and geographies.

Although there are a number of caveats and limitations, this investigation represents an important step in understanding the impact of meth and other illicit drug production on home prices. The value of lab decontamination in particular, will be an important issue in the coming years as more states consider adoption of mandatory decontamination legislation. We hope that this investigation spurs further research into this issue.

Table 2.1. Summary statistics for hedonic function explanatory variables

Variable	$D^{0.1}=1$ $(n=1806)$	$D^{0.3}=1$ $(n=8025)$	All Homes $(n=18819)$
SCORE	77.8256	80.3690	83.3700
	(16.6590)	(15.6531)	(15.8941)
BATHROOMS	1.6390	1.6688	1.8085
	(0.7483)	(0.7090)	(0.7069)
BEDROOMS	2.8488	2.8561	2.9482
	(0.9109)	(0.7940)	(0.7256)
SQUAREFT	1.3116	1.3249	1.4076
	(0.4936)	(0.4770)	(0.4892)
ACRES	0.1990	0.2088	0.2314
	(0.1902)	(0.3518)	(0.3536)
$\ln(AGE)$	3.4504	3.2675	2.8784
	(1.2651)	(1.3261)	(1.4468)
ACTIVESELLER	0.2093	0.2249	0.2558
	(0.4069)	(0.4176)	(0.4363)
ACTIVEBUYER	0.0648	0.0501	0.0427
	(0.2462)	(0.2182)	(0.2022)
MANUFACTURED	0.0415	0.0432	0.0449
	(0.1996)	(0.2034)	(0.2070)
FEDBUYER	0.0006	0.0001	0.0001
	(0.0235)	(0.0112)	(0.0073)
FEDSELLER	0.0011	0.0006	0.0006
	(0.0333)	(0.0250)	(0.0242)
SCHOOL	0.2802	0.2866	0.2070
	(0.4492)	(0.4522)	(0.4052)

Table 2.2. Empirical results (binary distance and temporal variables)

	Pre-Discovery	Full Sample			Limited (sales within 0.3 miles)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$D^{0.1}$	-0.069***	-0.026***	-0.003	-0.004	0.007	0.005	0.005
	(0.026)	(0.007)	(0.014)	(0.014)	(0.015)	(0.015)	(0.017)
$D^{0.1} * \tau^{\text{Discovery}}$			-0.029**	-0.067***	-0.027*	-0.059***	-0.059**
			(0.015)	(0.019)	(0.016)	(0.021)	(0.026)
$D^{0.1} * \tau^{\text{Clean}}$				0.049***		0.043**	0.043**
				(0.016)		(0.018)	(0.019)
$D^{0.3}$	-0.164***	-0.046***	-0.029***	-0.028***			
	(0.014)	(0.005)	(0.009)	(0.009)			
$D^{0.3} * \tau^{\text{Discovery}}$			-0.021**	-0.016*	-0.000	0.003	0.003
			(0.009)	(0.010)	(0.011)	(0.012)	(0.014)
$D^{0.3} * \tau^{\text{Clean}}$				-0.007		-0.002	-0.002
				(0.007)		(0.009)	(0.013)
Constant	11.942***	10.610***	10.602***	10.604***	10.373***	10.378***	10.387***
	(0.013)	(0.025)	(0.026)	(0.026)	(0.056)	(0.056)	(0.091)
Observations	12,053	18,818	18,818	18,818	8,025	8,025	8,025
R-squared	0.092	0.628	0.629	0.629	0.577	0.578	0.694
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓
Census-Block Fixed Effects		✓	✓	✓	✓	✓	✓
Housing Characteristics		✓	✓	✓	✓	✓	✓
Restricted to 0.3 Miles					✓	✓	✓
Lab Area Clustered SE							✓
Excluding Post-Discovery Sales	✓						

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.3. Marginal implicit price for home attributes

	Full Sample			Limited (sales within 0.3 miles)	
	(2)	(3)	(4)	(5)	(6)
$D^{0.1} * \tau^{\text{Discovery}}$		-$4,425	-$9,030	-$3,549	-$6,873
$D^{0.1} * \tau^{\text{Clean}}$			$6,540		$4,674
SCORE	$1,319	$1,319	$1,317	$1,269	$1,266
BATHROOMS	$10,114	$10,133	$10,116	$10,901	$10,871
SQUAREFT	$50,349	$50,284	$50,303	$42,208	$42,231
ACRES	$25,653	$25,673	$25,695	$24,003	$24,022
$\ln(AGE)$	-$1,246	-$1,250	-$1,254	-$822	-$826

Table 2.4. Auxiliary models: alternative treatment and control specifications

	(1)	**(2)**	(3)	(4)	(5)	(6)	(7)
Treatment Distance:	0.1 Miles	**0.1 Miles**	0.1 Miles	0.1 Miles	0.2 Miles	0.2 Miles	0.2 Miles
Control Distance:	0.2 Miles	**0.3 Miles**	0.4 Miles	0.5 Miles	0.3 Miles	0.4 Miles	0.5 Miles
$D^{\text{Treatment}}$	-0.005	**-0.004**	0.002	-0.002	-0.006	0.003	-0.005
	(0.015)	**(0.014)**	(0.013)	(0.013)	(0.011)	(0.010)	(0.009)
$D^{\text{Treatment}} * \tau^{\text{Discovery}}$	-0.052**	**-0.067*** **	-0.068***	-0.063***	-0.042***	-0.040***	-0.033***
	(0.022)	**(0.019)**	(0.019)	(0.018)	(0.014)	(0.012)	(0.011)
$D^{\text{Treatment}} * \tau^{\text{Clean}}$	0.043**	**0.049*** **	0.037**	0.031**	0.024**	0.005	-0.002
	(0.018)	**(0.016)**	(0.016)	(0.016)	(0.012)	(0.010)	(0.010)
D^{Control}	-0.019*	**-0.028*** **	-0.049***	-0.039***	-0.026**	-0.049***	-0.036***
	(0.010)	**(0.009)**	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
$D^{\text{Control}} * \tau^{\text{Discovery}}$	-0.027**	**-0.016***	-0.012	-0.024***	-0.005	-0.004	-0.018**
	(0.013)	**(0.010)**	(0.009)	(0.008)	(0.011)	(0.009)	(0.009)
$D^{\text{Control}} * \tau^{\text{Clean}}$	0.002	**-0.007**	0.012**	0.025***	-0.012	0.014**	0.027***
	(0.011)	**(0.007)**	(0.006)	(0.006)	(0.009)	(0.007)	(0.006)
Constant	10.603***	**10.604*** **	10.614***	10.618***	10.597***	10.606***	10.608***
	(0.026)	**(0.026)**	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Observations	18,818	**18,818**	18,818	18,818	18,818	18,818	18,818
R-squared	0.628	**0.629**	0.629	0.629	0.629	0.629	0.629
Number of Census Block	449	**449**	449	449	449	449	449

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.5. Primary DD models with time since discovery

	(1) (Without Decontamination)	(2) (With Decontamination)
$D^{0.1}$	0.0017	-0.0030
	(0.0139)	(0.0139)
$D^{0.1} * \tau^{\text{Discovery}}_{\text{0-6 Months}}$	-0.0050	-0.0142
	(0.0336)	(0.0337)
$D^{0.1} * \tau^{\text{Discovery}}_{\text{6-12 Months}}$	-0.0671**	-0.0985***
	(0.0310)	(0.0325)
$D^{0.1} * \tau^{\text{Discovery}}_{\text{12-18 Months}}$	0.0009	-0.0377
	(0.0301)	(0.0324)
$D^{0.1} * \tau^{\text{Discovery}}_{\text{18-24 Months}}$	-0.0074	-0.0476
	(0.0285)	(0.0311)
$D^{0.1} * \tau^{\text{Discovery}}_{\text{24-30 Months}}$	-0.0311	-0.0672**
	(0.0281)	(0.0303)
$D^{0.1} * \tau^{\text{Discovery}}_{\text{30-36 Months}}$	0.0132	-0.0343
	(0.0302)	(0.0335)
$D^{0.1} * \tau^{\text{Discovery}}_{\text{36+ Months}}$	-0.0399**	-0.0892***
	(0.0159)	(0.0219)
$D^{0.1} * \tau^{\text{Clean}}$		0.0575***
		(0.0177)
$D^{0.3}$	-0.0282***	-0.0280***
	(0.0087)	(0.0088)
$D^{0.3} * \tau^{\text{Discovery}}_{\text{0-6 Months}}$	-0.0248*	-0.0230
	(0.0141)	(0.0141)
$D^{0.3} * \tau^{\text{Discovery}}_{\text{6-12 Months}}$	-0.0055	-0.0023
	(0.0140)	(0.0144)
$D^{0.3} * \tau^{\text{Discovery}}_{\text{12-18 Months}}$	-0.0281**	-0.0244*
	(0.0140)	(0.0146)
$D^{0.3} * \tau^{\text{Discovery}}_{\text{18-24 Months}}$	-0.0276*	-0.0226
	(0.0144)	(0.0150)
$D^{0.3} * \tau^{\text{Discovery}}_{\text{24-30 Months}}$	-0.0221	-0.0184
	(0.0145)	(0.0152)
$D^{0.3} * \tau^{\text{Discovery}}_{\text{30-36 Months}}$	-0.0161	-0.0116
	(0.0145)	(0.0153)
$D^{0.3} * \tau^{\text{Discovery}}_{\text{36+ Months}}$	-0.0226**	-0.0183*
	(0.0093)	(0.0109)
$D^{0.3} * \tau^{\text{Clean}}$		-0.0056
		(0.0078)
Constant	10.5983***	10.6007***
	(0.0256)	(0.0256)
Observations	18,818	18,818
R-squared	0.6297	0.630
Year FE	✓	✓
Census Block FE	✓	✓
Housing Characteristics	✓	✓
Restricted to Lab Areas		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.6. Primary model with clustered standard errors

VARIABLES	(1) Lab Area Clustered SE	(2) Census Block Clustered SE
$D^{0.1}$	0.005	-0.004
	(0.017)	(0.018)
$D^{0.1} * \tau^{\text{Discovery}}$	-0.059**	-0.067***
	(0.026)	(0.025)
$D^{0.1} * \tau^{\text{Clean}}$	0.043**	0.049**
	(0.019)	(0.021)
$D^{0.3}$		-0.028**
		(0.012)
$D^{0.3} * \tau^{\text{Discovery}}$	0.003	-0.016
	(0.014)	(0.012)
$D^{0.3} * \tau^{\text{Clean}}$	-0.002	-0.007
	(0.013)	(0.010)
Constant	10.387***	10.620***
	(0.091)	(0.051)
Observations	8,025	18,818
R-squared	0.694	0.719
Year FE	✓	✓
Census Block FE	✓	✓
Lab Area Clustered SE	✓	
Census Block Clustered SE		✓
Housing Characteristics	✓	✓
Restricted to Lab Areas	✓	✓

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.7. Auxiliary Models

	(1)	(2)	(3)	(4)	(5)
DISTANCE					0.219***
					(0.051)
$D^{0.1}$	-0.036***	-0.033**	0.002	0.002	
	(0.014)	(0.014)	(0.016)	(0.016)	
$D^{0.1} * \tau^{disc}$	-0.083***	-0.110***	-0.025*	-0.051***	
	(0.008)	(0.014)	(0.014)	(0.019)	
$D^{0.1} * \tau^{clean}$		-0.072***		-0.018	
		(0.009)		(0.015)	
$D^{0.3}$	-0.024***	-0.020**			
	(0.009)	(0.009)			
$D^{0.3} * \tau^{disc}$	-0.050***	-0.040***	-0.005	-0.003	
	(0.005)	(0.008)	(0.012)	(0.013)	
$D^{0.3} * \tau^{clean}$		-0.052***		-0.007	
		(0.005)		(0.013)	
Constant	10.590***	10.591***	10.378***	10.382***	10.297***
	(0.026)	(0.026)	(0.056)	(0.056)	(0.063)
Observations	18,818	18,818	8,025	8,025	6,766
R-squared	0.629	0.629	0.579	0.580	0.583
Year FE	✓	✓	✓	✓	✓
Census Block FE	✓	✓	✓	✓	✓
Housing Characteristics	✓	✓	✓	✓	✓
Restricted to Sales w/i 0.3 Miles			✓	✓	✓

Figure 2-1. Visual depiction of identification strategy

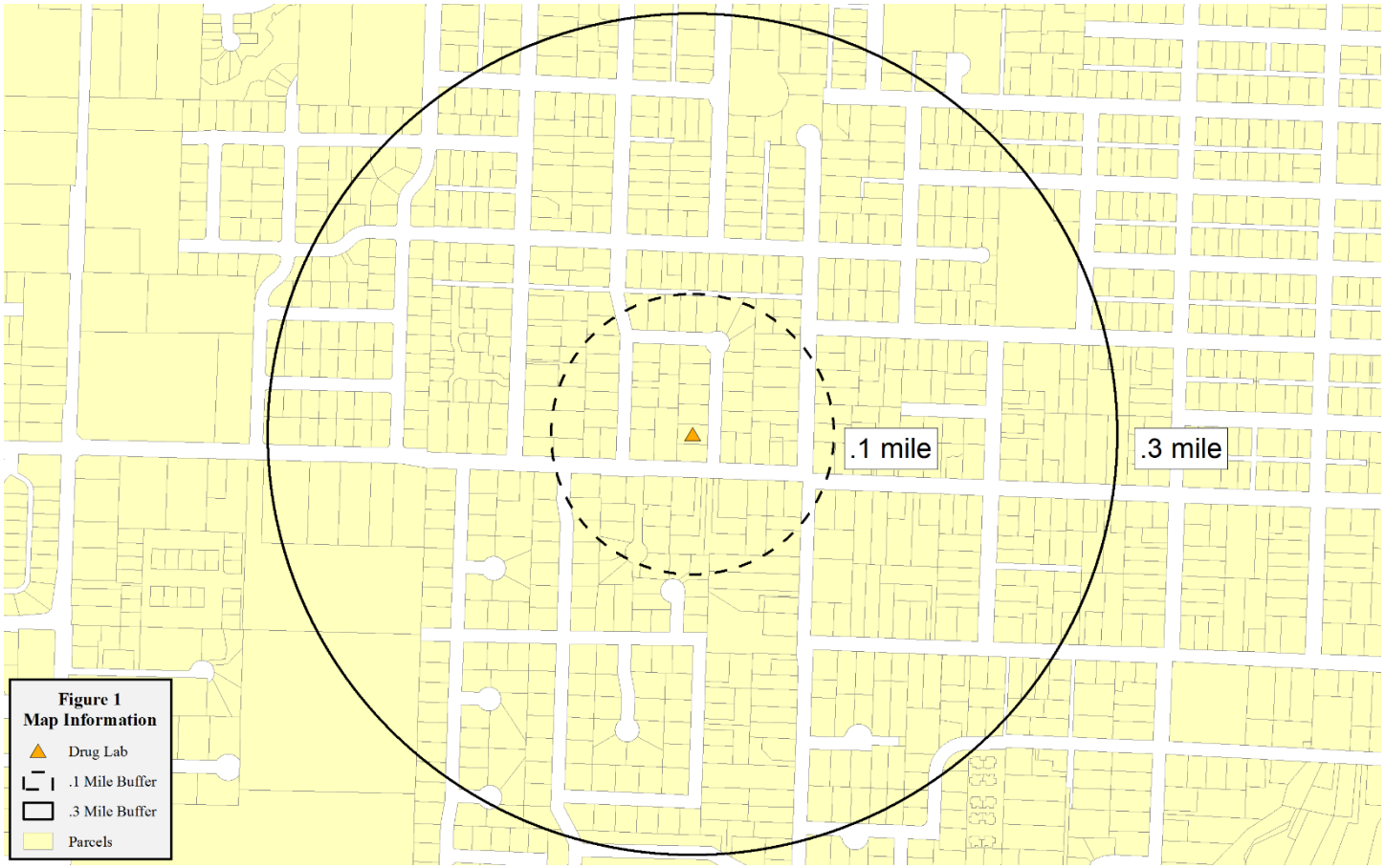


Figure 2-2. Methamphetamine labs in Linn County, Oregon (1996-2013)

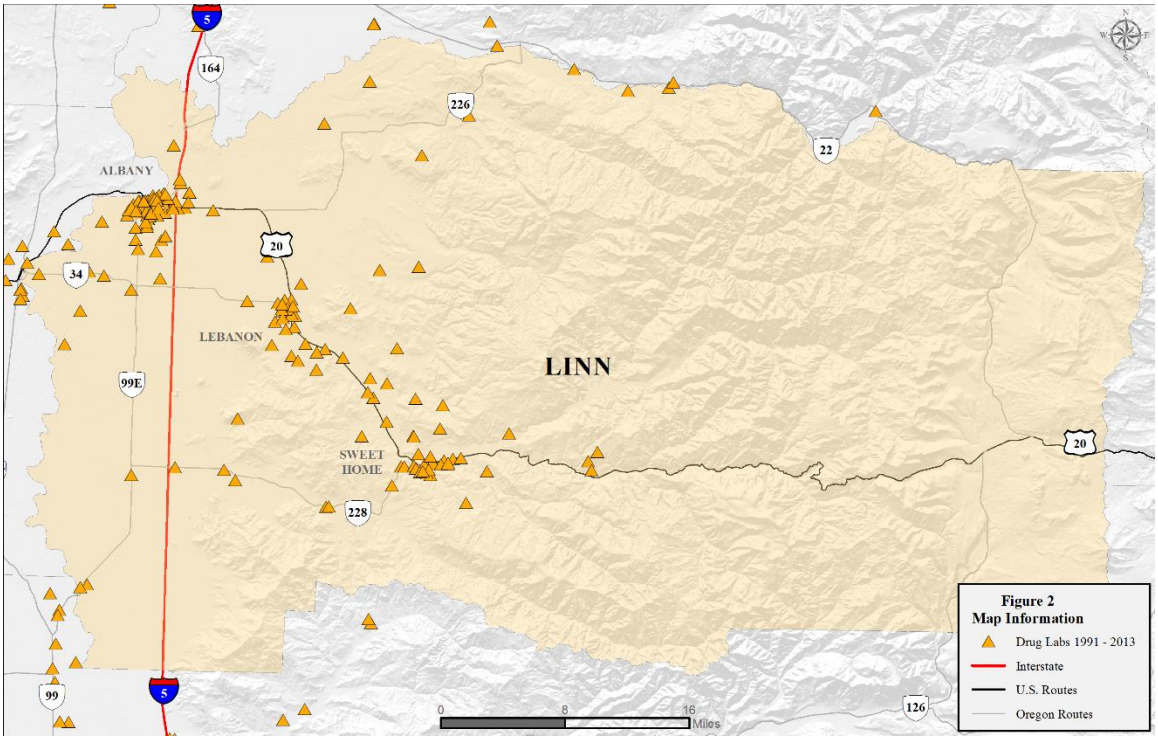


Figure 2-3. Property sales in Linn County, Oregon (1999-2013)

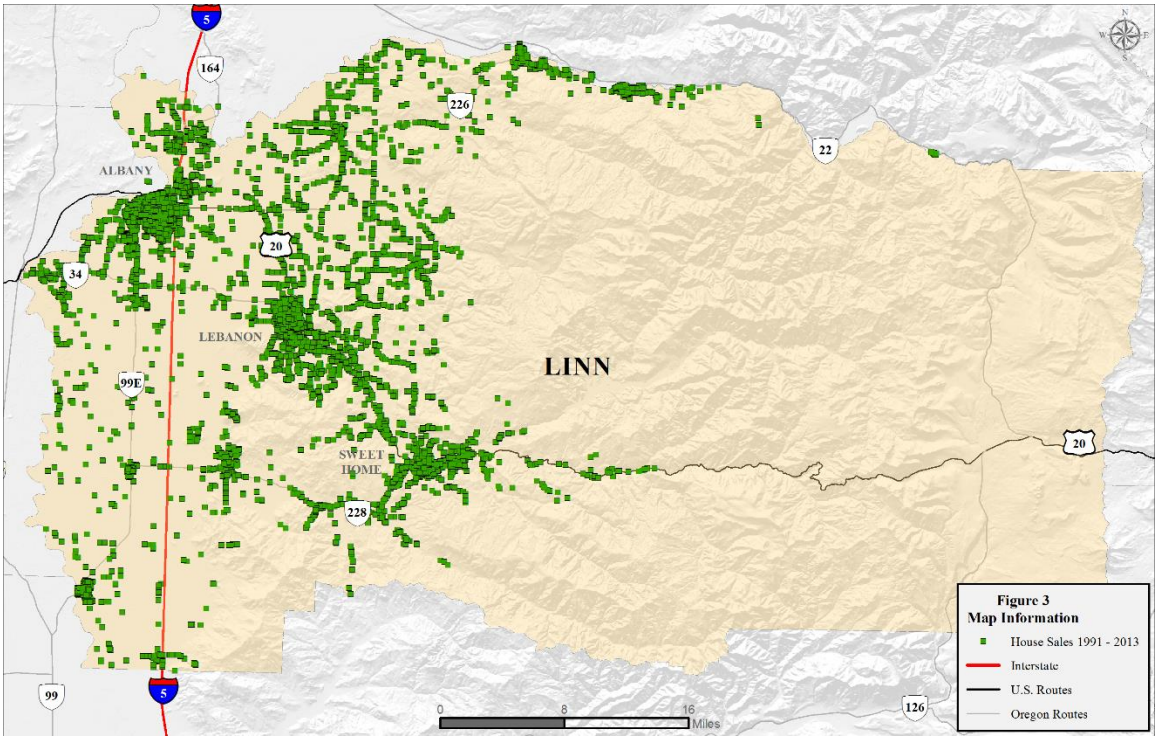
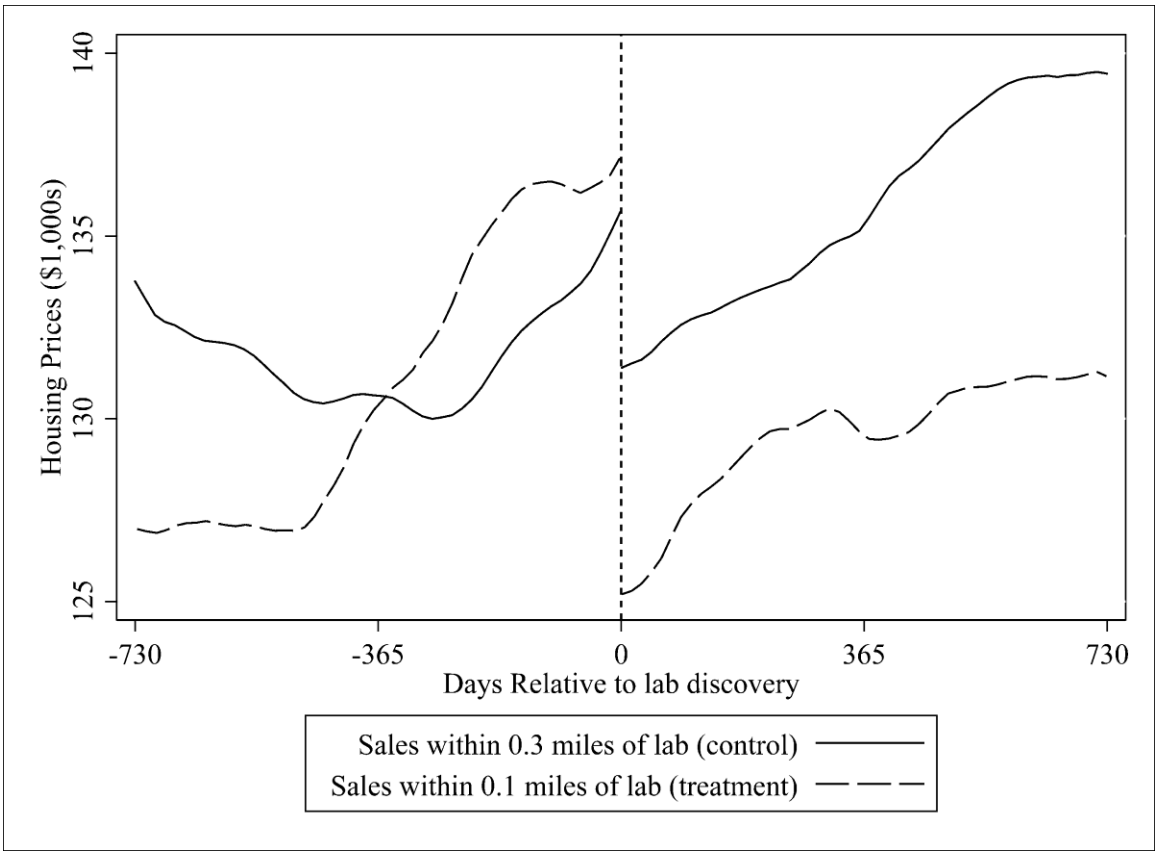


Figure 2-4. Price trends before and after lab discovery



Chapter 3: The Impact of Behavioral Risk Reduction Interventions on Willingness to Pay to Avoid Sexually Transmitted Infections: A Stated Preference Study of Justice-Involved Youth

3.1 Introduction

Every year in the US over one-third of all deaths can be attributed to modifiable behaviors such as smoking, alcohol abuse, poor diet and risky sexual behavior (Schroeder, 2007). The treatment of chronic morbidity linked to these behaviors accounts for over 75% of all health care costs (Fisher et al., 2011). To mitigate the burden associated with preventable disease numerous behavioral public health interventions have been implemented in the US, addressing a diverse range of health risks (e.g., childhood obesity (Durant, Baskin, Thomas, & Allison, 2008; Stice, Shaw, & Marti, 2006); problem drinking (Cuijpers, Riper, & Lemmers, 2004; Dinh-Zarr, Diguiseppi, Heitman, & Roberts, 1999); and tobacco use (Biglan, Ary, Smolkowski, Duncan, & Black, 2000; Bruvold, 1993; Siegel, 2002)). Risky sexual behavior, in particular, poses an increasingly burdensome cost upon the healthcare system. One-third of all Americans will contract a Sexually Transmitted Infection (STI) at some point in their lives (Summers, Kates, & Murphy, 2002) and the lifetime treatment costs resulting from a single year of STIs in the US exceeds $15.6 billion. Moreover, adolescents and young adults, the least-experienced and most-vulnerable portion of the sexually-active US population, contract a

disproportionately large number of new STIs (H. W. Chesson, J. M. Blandford, T. L. Gift, G. Tao, & K. L. Irwin, 2004).

In attempting to modify sexual risk behavior, it is well known that interventions that are based on validated theories of health behavior are more successful than those that are not (Glanz & Bishop, 2010). Reviews and meta-analyses indicate that the Theory of Planned Behavior (TPB), a widely-used theoretical perspective, is particularly successful (Armitage & Conner, 2001; Sutton, 2004). The TPB defines the relationship between beliefs and behavior and posits that behaviors result most proximally from intentions, which are in turn determined by attitudes, social norms, and self-efficacy/perceived control (Ajzen, 1991). In addition to demonstrating clinical efficacy, theory-based behavioral interventions have been shown to be cost-effective when evaluated from an economic perspective (Dealy, Horn, Callahan, & Bryan, 2013; Wang et al., 2000). Moreover, research at the intersection of economics and psychology is proving to be mutually beneficial. For example, economic incentives such as cash payments and lotteries are increasingly being incorporated into health behavior interventions (Dallery, Silverman, Chutuape, Bigelow, & Stitzer, 2001; Dunn, Saulsgiver, & Sigmon, 2011; Gray et al., 2011; Operario, Kuo, Sosa-Rubí, & Gálarraga, 2013). Additionally, while economic models do not generally consider the role of attitudes and intentions independently, empirical health economics studies have found that individuals respond to incentives when making choices about health risk behavior, including choices about risky sex (Klick & Stratmann, 2003, 2007; Levine, 2001), smoking (Gruber & Zinman, 2001) and marijuana use (Pacula et al., 2000). However, when modeling risky health behavior,

economic models typically regard preferences as stable and heterogeneity in behavior is typically explained using discount rates (Frederick, Loewenstein, & O'donoghue, 2002).[8]

One method that can be used to better understand the behavioral impact of a risky health behavior intervention is a survey method known as Contingent Valuation (CV). This method is a long-standing economic preference elicitation technique, which is increasingly being utilized outside of standard economic contexts to elicit economic preferences when direct markets do not exist. A number of studies have utilized the CV method in the context of STI. For instance, Galárraga, Sosa-Rubí, Infante, Gertler, and Bertozzi (2014) use the CV method to estimate individuals' Willingness To Accept (WTA) compensation for participating in HIV/AIDS interventions and Gupta and Trivedi (2014) estimate the Willingness To Pay (WTP) for health insurance for people living with HIV in India. Additionally, Poulos et al. (2011) estimate mothers' WTP to vaccinate their children against human papillomavirus. Furthermore, the CV method has been used to evaluate how different levels of information impact WTP for health programs (Protière, Donaldson, Luchini, Moatti, & Shackley, 2004).

In this study, we build upon the existing literature by using the CV method to test if behavioral interventions (or more generally attitudes, intentions and information) impact the perceived costs of risky behavior. Specifically, data were obtained through Project MARS (Motivating Adolescents to Reduce Sexual Risk; (Callahan, Montanaro, Magnan, & Bryan, 2013)), which is a randomized, sexual risk-reduction intervention for justice-involved youth designed to change TPB constructs of attitudes towards condom

[8] Significant attention has been given to the appropriate type of discount rate (i.e., exponential, hyperbolic, quasi-hyperbolic, etc.), and whether the discount rate (in any form) can explain differences in risky health behaviors.

use, norms supportive of condom use, self-efficacy for condom use, and intentions to use condoms. As part of this trial, participants were asked questions eliciting their WTP to avoid three different categories of STI (curable, incurable and fatal) prior to the intervention and three months after the intervention. This unique pre-post CV survey design is used to test if the MARS intervention changed participants' WTP to avoid STI. Additionally, because WTP was elicited for multiple levels of infection severity, both before and after the intervention was received, this study contributes to an ongoing debate in the health economic literature on what is referred to as 'scope sensitivity' (or if individual's elicited WTP is sensitive to the level or nature of the good valued).

Overall, results indicate that the MARS intervention did in fact increased participants' WTP to avoid both incurable and fatal STI. Thus, evidence is found that perceived costs may not be stable, and can be changed by behavioral interventions. Additionally, after receiving the intervention, this unique cohort of justice involved youth were found to be sensitive to scope, providing evidence of construct validity.

3.2 Background on Contingent Valuation

A number of stated preference survey methods are used to estimate the monetary value of goods and services that are not generally traded in markets (Bishop, Champ, & Mullarkey, 1995). Within this broader set, CV is the most commonly used preference elicitation approach (Boyle, 2003; Carson, 2012). CV surveys elicit individuals' WTP or WTA compensation responses using various survey modes and elicitation formats. The most direct elicitation format, open-ended, simply asks individuals to provide their

maximum WTP. Alternatives include a variety of close-ended or discrete choice formats to indirectly measure WTP or WTA, such as voting responses to a proposed public goods referendum where the tax payment is varied across the sample (Boyle, 2003; Carson, 2012).

As applications continue to expand, the CV method has been used extensively in a variety of contexts, including a growing literature in health care and services. The increased utilization in health care can be explained by the similarity of health care to goods to environmental goods: both will often require policy interventions when the market fails to allocate efficiently (Hanley, Ryan, & Wright, 2003). CV studies in the context of health care include; valuation of alternative treatments for health conditions (Doyle et al., 2012), parents valuation of healthcare for their children (Poulos et al., 2011; Vermaire, Van Exel, Van Loveren, & Brouwer, 2012) alternative healthcare delivery programs (Callan & O'Shea, 2015; Shono, Kondo, Ohmae, & Okubo, 2014).

Although well-constructed CV studies often exhibit considerable reliability (e.g., temporal stability), or meet various validity indicators (e.g., expected responses to payment amounts or income effects), there are persistent concerns about potential hypothetical bias (where stated value differs from true value) (Haab, Interis, Petrolia, & Whitehead, 2013). Further, there remains debate about whether elicited WTP responses are sensitive to positive or negative changes in the elicited good (e.g. size, or geographic scale or levels of impacts or severity). Tests for the sensitivity of WTP responses to changes in goods are commonly referred to as scope tests (Carson, 2012; Hausman, 2012; Kling, Phaneuf, & Zhao, 2012). For example, if a respondent is presented with two

different quantities of an identical good, then WTP for the larger quantity should exceed WTP for the smaller quantity.

It is now common for studies to include explicit tests of scope sensitivity (Carson & Mitchell, 1995). Passing a scope test provides evidence of a CV survey's construct validity, which involves 'theoretical and intuitive prior expectations about the relationship that should exist between variables' (Bishop, 2003). This requires that the values elicited from the survey are capturing the preferences of the good intended. If elicited preferences do not conform to standard economic theory, then questions arise as to the validity of the survey instrument. The most commonly applied scope test is a within-subject comparison of WTP for alternative quantities of the hypothetical good. For instance, willingness-to-pay for a health risk reduction should be positively associated with the magnitude of the risk reduction and severity of the health risk (Hammitt & Graham, 1999).

Scope tests require that individuals assign a value to alternative levels of the good, so it is important for the survey instrument to describe clearly differentiated levels of precisely the same good. Take for example the value of benefits conferred by a government program. The valuation of these benefits consist not only of the value of the program delivered with certainty, but also the probability an individual assigns to the likelihood of the government being able to deliver on their promises. As Carson (2012) points out, "… for a substantial fraction of the public, the likelihood of the government delivering on very large projects can be perceived to be much lower than that for smaller projects,". If tests of scopes in a CV study include increasing the quantity or quality of a good beyond realistic levels, then respondents may not value the unrealistically large

change more than a modest, but realistic change. In a CV study of alternative government health-programs, Olsen, Donaldson, and Pereira (2004b) test the sensitivity of WTP for heart attack risk reductions to alternative levels of reduction (10%, 20%, and 40%). The authors find that WTP *decreases* with the size of the risk reduction, with the largest WTP elicited for the 10% reduction. The authors conclude that respondents' are insensitive to scope in the context of evaluating heart attack risk reduction. However, an important observation from this study is that the number of zero bids increases dramatically with the size of the promised reduction, which may have changed the character of the good in unintended ways. For example, the spike in zero bids could reflect disbelief in the government's ability to deliver such high reductions in risk.

In a meta-analysis of CV studies and scope effects, Carson (1997) finds that a majority of the studies that included scope tests (at that time, 31 out of 35) were able to reject the scope insensitivity hypothesis. Additionally, a number of CV studies across a variety of health and healthcare contexts have found scope sensitivity (Bobinac, van Exel, Rutten, & Brouwer, 2014; Greenberg, Bakhai, Neumann, & Cohen, 2004; van den Berg, Brouwer, Exel, & Koopmanschap, 2005). However, some counterexamples exist (Olsen, Donaldson, & Pereira, 2004a; Olsen, Røgeberg, & Stavem, 2012; Søgaard, Lindholt, & Gyrd-Hansen, 2012). Whitty (2012) advocates for additional investigation into the underlying reason for when we do not find scope sensitivity.

3.3 Data

3.3.1 Data Collection

Data used in this study were collected from questionnaires administered during the clinical trial phase of Project MARS (Callahan et al., 2013), between July 2010 and March 2012. Project MARS was an intervention designed to reduce sexual risk behavior among justice-involved youth. The intervention was delivered to justice-involved adolescents (ages 14-18) in a short-term juvenile detention center in the South-western US. Research assistants visited the detention center on a weekly basis and provided all new arrivals the opportunity to participate. The program was described as a research study conducted by the University of New Mexico. Adolescents who expressed interest in the study met individually and privately with a research assistant to complete informed-consent documents. Upon receipt of adolescent consent, parent/guardian consent was obtained and recorded via telephone for each adolescent, consistent with previous studies (Schmiege, Broaddus, Levin, & Bryan, 2009). This intervention was based on previously successful HIV/STD risk reduction interventions conducted with young adults (Bryan, Schmiege, & Broaddus, 2009) and was comprised of a single three-hour session, with up to six justice-involved adolescents participating in each intervention group.

After completing the baseline assessment, participants were randomly assigned to receive one of the three group-based interventions. Participants received $30 for completing the baseline questionnaire and participating in the intervention. Those who completed the three-month follow-up questionnaire received an additional $40 upon completion. This project was approved by the University of New Mexico's Human

Research Review Committee and, because participants were in a detention facility, the national Office of Human Research Protections. A certificate of confidentiality was obtained from the National Institutes of Health (NIH) to further protect participant privacy.

3.3.2 CV Survey Design

MARS participants answered a series of CV survey questions eliciting their maximum WTP to avoid three different categories of STIs (curable, incurable, and fatal). All questionnaires were administered using the ACASI (Audio Computer Assisted Self-Interview) survey method. The same survey instrument was administered to participants both prior to the intervention and at three months after the intervention. WTP questions were open-ended, but bounded between $0 and $100 000. The exact wording appeared in the survey instrument as:

> **How much is the maximum you would pay to not get a curable STD (curable STDs are things like Chlamydia and Gonorrhea)?**
>
> I would pay $_____.
>
> **How much is the maximum you would pay to not get an incurable, non-fatal STD (incurable, non-fatal STDs are things like Herpes and HPV)?**
>
> I would pay $_____.

How much is the maximum you would pay to not get a fatal STD (A fatal STD is HIV/AIDS)?

I would pay $_____.

All respondents answered the three valuation questions in the same order: curable, incurable and fatal. Each question was presented separately and respondents saw only one question on the computer screen at a time. The three goods are all defined in terms of avoiding an STI, but with distinct categories of impact severity. Utilizing terminology from Carson and Mitchell (1995), each respondent is presented a bottom-up valuation sequence of avoiding infection with increasing negative health impact or severity in the scope of the STI. This allows for a within-sample or internal test of scope (Carson & Mitchell, 1995).

3.4 Empirical Approach

3.4.1 Theoretical Considerations

The WTP to avoid an STI can be defined using the following indirect utility function:

$$V\left(P, STI_j^0, M - WTP_j\right) = V\left(P, STI_j^1, M\right) = u^1 \tag{3.1}$$

where $V(\cdot)$ is the indirect utility function, P is a vector of prices for marketed goods (i.e., all other goods that individuals purchase with their income), STI_j^0 represents the

current level of respondent infectivity, where the superscript indicates whether the respondent is infected ($0 =$ uninfected), and the subscript $j = \{c, inc, f\}$ represents the severity level, curable, incurable and fatal infections, respectively. Additionally, in this model, M indicates income, u^1 is the reference level of utility (corresponding to utility if infected with an STI), and WTP_j is the income adjustment that would make an individual indifferent between the two states (infected with original income and uninfected with income adjustment). Further, WTP_j is interpreted exactly as it was presented to respondents: the maximum WTP to avoid STI_j. Thus, in this context, WTP_j is a Hicksian equivalent welfare change measure (A. M. Freeman, 2003).

Alternatively, the Hicksian equivalent welfare change measure, WTP_j, can be presented explicitly as the difference between two expenditure functions:

$$WTP_j = \left| e\left(P, STI_j^0, u^1\right) - e\left(P, STI_j^1, u^1\right) \right| \tag{3.2}$$

It is assumed that variation in respondents' WTP_j is determined by the category (j) of STI for which it is elicited, as well as subjects' socioeconomic characteristics and subjective risk perceptions. The WTP function can thus be represented as

$$WTP_{i,j,t} = g\left[X_i, STI_{j,t} \right] \tag{3.3}$$

where X_i is a vector of socioeconomic characteristics including personal experiences, and $STI_{j,t}$ is a vector of binary variables corresponding to infection category (i.e., $j = \{c, inc, f\}$) and time period (i.e., $t = \{0,1\}$, where 0 indicates pre-intervention and 1 indicates post-intervention).

3.4.2 Econometric Model

An econometric model is specified to estimate the impact of the MARS intervention on participants' (log-transformed) WTP to avoid STIs. To test the impact of the intervention on participants' WTP to avoid infections, and to test sensitivity to scope (infection severity), log-transformed WTP estimates are transformed back into dollars, generating median WTP estimates, with standard errors calculated using the Delta method.

WTP was elicited using an open-ended format and the survey restricted participants' response to the range of values between \$0 and \$100 000. To account for the censored nature of the dependent variable, a double-bounded Tobit model (Awad & Holländer, 2010; Martínez-Paz & Perni, 2011) is used with the following specification

$$\ln\left(WTP^{*}_{i,j,t}\right) = X_i^{'}\beta + STI^{'}_{j,t}\delta + \varepsilon_{i,t} \tag{3.4}$$

where $\ln\left(WTP^{*}_{i,j,t}\right)$ is respondent i's $\left(i = 1,...,N\right)$ log-transformed latent maximum WTP to avoid STI_j elicited either prior to the intervention ($t = 0$), or three months after receiving the intervention ($t = 1$). A random-effect error term ($\varepsilon_{i,t}$) is included in order to account for the fact that each respondent enters the dataset more than once and includes an individual-specific error component, as well as an idiosyncratic error term. Time-invariant socioeconomic characteristics are represented by the X_i vector. Included within the X_i vector are binary variables for *GENDER* (=1if male) and *WHITE* (=1 if respondent identified as white), which are included in order to account for heterogeneity

in both race and gender. Note that participant ethnicity is accounted for with only a single binary variable. Furthermore, binary variables for $STITEST$ (=1 if respondent tested positive for Chlamydia or Gonorrhea prior to the intervention), $PREGNANCY$ (=1 if respondent has been involved in a pregnancy), and $ABORTION$ (=1 if respondent was involved in a pregnancy which was aborted) are included to account for heterogeneity associated with negative sexual consequences.

3.4.3 Intervention Effects and Scope Tests

Predicted median WTP estimates are first used to the test the effect of the intervention on participants' WTP. Recall that participants answered the CV questions both before and after the intervention, which allows us to test the impact of the intervention using the following null and alternative hypotheses:

$$\begin{aligned} H1_0 &: WTP_{j,0} = WTP_{j,1} \\ H1_A &: WTP_{j,0} \neq WTP_{j,1} \end{aligned} \tag{3.5}$$

Note that this test represents three separate two-tailed t-tests (one for each STI category, $j = \{c, inc, f\}$) that test if participants' WTP to avoid an STI increases after receiving the intervention ($t = 1$ versus $t = 0$).

In addition, WTP estimates are also used to test participant's sensitivity to the severity of infection (or sensitivity to scope). In the context of STI acquisition, as the severity of negative health impacts increase, the perceived cost, or WTP to avoid these impacts should also increase. To test if respondents' WTP did in fact increase with severity level, the following null and alternative hypotheses are used:

$$H2_{01}: WTP_{c,t} = WTP_{inc,t} \quad \text{and} \quad H2_{02}: WTP_{inc,t} = WTP_{f,t}$$
$$H2_{A1}: WTP_{c,t} \leq WTP_{inc,t} \quad H2_{A2}: WTP_{inc,t} \leq WTP_{f,t} \tag{3.6}$$

Each scope test (one at baseline data and the other one after the intervention) is a combination of two, one-tailed t-tests, which test whether participants are willing to pay more to avoid more severe STIs. If WTP is insensitive to STI category, WTP would not increase from curable to incurable and from incurable to fatal.

3.4.4 Robustness Tests

In order to test the robustness of the empirical models, a number of auxiliary models are estimated. First, single-period models are estimated to detect the difference in WTP for different levels of STI severity in each period (pre- and post-intervention) separately. Again, log-transformed willingness to pay is estimated with a double-bounded Tobit model:

$$\ln\left(WTP_{i,j}^{*}\right) = X_i^{'}\beta + STI_j^{'}\delta + \varepsilon_i \tag{3.7}$$

The next specification is interested in the detecting the impact of the intervention treatment for each STI separately. Similar to the primary model, this model estimates a random effects double-bounded Tobit model:

$$\ln\left(WTP_{i,t}^{*}\right) = X_i^{'}\beta + STI_t^{'}\delta + \varepsilon_{i,t} \tag{3.8}$$

3.5 Results

3.5.1 Summary Statistics: Project MARS Participants

264 justice-involved youth participated in the intervention and baseline interview, and 206 participants completed the three-month post-intervention questionnaire. Two of the 206 participants who completed the three-month follow-up did not complete the WTP questions, and are excluded from the analysis. Thus, 204 total participants are included in the analysis.

Summary statistics are presented in Table 3.1. The majority of the MARS participants utilized in this analysis identified as either Hispanic (71.1%) or White (24.5%). Other ethnicities represented in the sample include Native American (7.8%), Black (6.9%) and Asian or Pacific Islander (<1%). This distribution is roughly consistent with the population of juvenile offenders in the South-western US (Puzzanchera, Sladky, & Kang, 2011). Additionally, approximately 23% of participants were female. Recent statistics on justice-involved youth in this region suggest that females comprise approximately 14% of the population (Sickmund, Sladky, Kang, & Puzzanchera, 2011). Thus, young women might be slightly overrepresented in the sample. On average, participants were just over 16 years old and just under a 9^{th} grade education.

Prior to the intervention, approximately 8% of the subjects tested positive for either Gonorrhea $(n = 6)$ or Chlamydia $(n = 12)$, and one subject tested positive for both. All participants who tested positive for Chlamydia or Gonorrhea were treated for their infections by project staff under the direction of an adolescent medicine specialist. Over one-third of the participants (38%) reported that they had been involved in a pregnancy, and 9% reported having been involved in a pregnancy that was ultimately aborted. Both

male and female participants were asked questions regarding pregnancies. However, note that this number could include underreporting as it is possible that male participants did not have knowledge of their involvement in a pregnancy.

3.5.2 Tobit Model Estimation

Table 3.2 presents the results from the double-bounded Tobit model. First, note that the baseline STI and intervention-condition represents the WTP for a curable infection prior to the intervention (i.e., $j = c$ and $t = 0$). The variable $INCURABLE$ indicates a change in severity of the infection in the pre-intervention period from curable to incurable (i.e., a change from $j = c$ to $j = inc$) and $FATAL$ indicates a change in the severity of infection in the pre-intervention period from curable to fatal (i.e., a change from $j = c$ to $j = f$). Changes in the elicited WTP to avoid an infection by severity of infection after the intervention was received are represented using $*INTERVENTION$. Thus, the $CURABLE*INTERVENTION$ parameter represents the difference in the WTP to avoid a curable STI between the pre-intervention and three-month post-intervention. Finally, $INCURABLE*INTERVENTION$ and $FATAL*INTERVENTION$ variables represent both a change in infection severity and intervention condition from the baseline STI and intervention-condition.

Overall, all of the estimated severity-intervention interaction parameters are significant at or beyond the 0.01 level except the estimated $INCURABLE$ parameter. This suggests that both the severity of infection and receiving the intervention are determinants of WTP to avoid infections (significance between different intervention

groups is evaluated in the next section). The lack of statistical significance of the estimated *INCURABLE* parameter indicates that participants were not willing to pay more to avoid an incurable infection than a curable infection *before* the intervention. In terms of the other explanatory variables, first, the estimated coefficient for *WHITE* is positive and significant at the 0.05 level. The estimated coefficient for *GENDER* is not significant. This is potentially surprising, given that the costs (as well as single-act transmission probabilities) for nearly all STIs are greater for females than males. However, it is plausible that participants do not have full knowledge about treatment costs or do not plan on paying for treatment themselves. Although the estimated coefficient for *PREGNANCY* is not significant, the estimated coefficient for *ABORTION* is positive and significant at the 0.05 level, indicating that participants that have experienced an abortion had a higher WTP to avoid an infection. The estimated coefficient for *STITEST* is not significant, indicating that prior experience with curable infections did not significantly alter WTP to avoid infections. Finally, to evaluate the robustness of these findings, a number of additional model specifications were estimated, including separate random-effects Tobit models for each STI category, as well as separate cross-sectional Tobit models for each STI category. Overall, while there were some small changes in the significance of the explanatory variables, the impact of both infection severity and the intervention are robust across alternative model specifications.

3.5.3 Intervention Effects and Scope Tests

Table 3.3 presents the predicted median WTP to avoid obtaining an STI and the difference in WTP for STI severity groups and time periods. In this table the first column presents median WTP estimates. The columns to the right of the first two columns present a matrix of estimated WTP differences and significance levels, which are used to test Eq. 3.5 and Eq. 3.6.

In terms of the main results of our study, the median predicted WTP before the intervention was received is $331.33, $523.26 and $1 720.72 for curable, incurable and fatal STI respectively and following the intervention, these median predicted WTP estimates had increased to $855.40, $2 691.73 and $6 643.15. Thus, following the intervention, MARS participants' WTP to avoid an infection increased by $524.07 for curable (~158% increase), $2 168.47 for incurable (~414% increase), and $4 922.43 for fatal infections (~286% increase). In terms of significance of these results, although the change in WTP for a curable STI more than doubles following the intervention, this difference is not statistically significant. Alternatively, following the intervention, the change in WTP for incurable and fatal STIs are both significant at the 0.05 level. Thus, for these types of infections, participants were willing to pay significantly more after receiving the intervention, which supports the alternative hypotheses entailed in Eq. 3.5.

Next, the sensitivity to infection severity (i.e., scope sensitivity) is evaluated both before and after the intervention was received. Recall that this test (Eq. 6) jointly tests the change in WTP from curable to incurable and the change in WTP from incurable to fatal. First, evaluating this test prior to the intervention, respondents' WTP to avoid incurable STI exceeds that of curable STI by $191.93 and their WTP to avoid fatal STI exceeds the WTP to avoid incurable STI by $1 197.46. In terms of statistical significance, while the

difference between incurable and fatal STI is significant at the 0.05 level, the difference in median predicted WTP between curable and incurable STI is not significant. Thus, while WTP to avoid is always increasing with the severity of impacts, prior to the intervention participants' WTP to avoid these types of infections were not significantly different. Next, applying this test to predicted WTP estimates following the intervention, participants' WTP to avoid incurable STI exceeds that of curable STI by $1 836.33 and the WTP to avoid fatal STI exceeds the WTP to avoid incurable STI by $3 951.42, which are significant at the 0.05 and 0.1 levels respectively. Thus, not only are the WTP estimates considerably larger after the intervention, they also pass the scope test at the 0.05 level, which supports the alternative hypothesis in Eq. 6.

3.5.4 Robustness Checks

First, the primary model is adapted to explore how STI severity varies within each period. Results from this model are reported in Table 3.4. For both models, the baseline STI is curable. The coefficients on $INCURABLE$ and $FATAL$ represent the change from WTP for a curable and WTP for an incurable or fatal STI, respectively. In the pre-intervention model, $INCURABLE$ is not significant, but $FATAL$ is positive and highly significant. This result supports the findings from the primary model and the median WTP estimates. Prior to the intervention, MARS participants did not value avoidance of these two STIs differently. The post-intervention model also support the findings from the primary model. Following the intervention, WTP for avoidance of both $INCURABLE$ and $FATAL$ STIs are significantly higher than $CURABLE$.

Auxiliary models estimating the impact of treatment for each STI separately are presented in Table 3.5. The primary specification shows that the WTP for each STI increases following the intervention (all significant beyond the 1% level). The results from this auxiliary specification support the findings of the primary model. For each STI category, WTP increases significantly in response to the intervention.

3.6 Discussion

In this study, the CV stated preference survey method is used to evaluate the impact of a behavioral risk reduction intervention for justice-involved youth on the perceived value of STI avoidance. The results suggest that not only did the intervention increase MARS participants' WTP to avoid both incurable and fatal STI but also, after receiving the intervention, participants' WTP were more sensitive to infection severity (sensitive to scope). Thus, evidence is found that behavioral interventions may change the perceived cost that individuals associate with the outcomes of risky behavior. These results add to a growing literature about how information (in this case, in terms of attitudes, social norms, self-efficacy and perceived control) can affect perceived costs, and hence may be an important component of economic models of risky health behavior choices.

This paper also contributes to an ongoing debate in the health economics literature regarding the appropriate contexts for application of the CV method (Gyrd-Hansen, Kjær, & Nielsen, 2012; Haab et al., 2013). Prior to the intervention, elicited WTP increased with infection severity, but was not statistically different between curable and incurable infections. Following the intervention, WTP was more sensitive to scope of infection

severity. In other words, the elicited preferences from this unique sample (justice-involved youth), evaluating a complex good (STI prevention, with varying scope in severity of negative health impacts) exhibited statistically significant scope effects. These results suggest that an impact of the MARS intervention is causing the participants to value STI avoidance in a more rational fashion. Although the population of this study may limit the generalizability of the point-estimates on WTP, the lack of numeracy and formal education should serve to increase confidence in the estimates from the scope tests and the impact of the intervention on WTP. The intervention did not discuss explicitly discuss probabilities or relative expenses of the diseases.

One should exercise caution when interpreting these results as this study was limited by a number of factors. First, the complexity of the survey questions limits the direct inference that can be derived from our point estimates. Future work could reduce the required cognitive processing, perhaps by using a dichotomous choice survey method. For instance, Galárraga et al. (2014) and Olsen et al. (2012) use a double-bounded model to more accurately simulate market conditions and potentially reduce cognitive complexity. Additionally, when using an open-ended format it is not clear that the $0 to $100 000 bounding is needed (especially considering that participants may be willing to pay more than the upper bound to avoid fatal STI). Second, preference would be more accurately elicited if the STI avoidance mechanism was better defined (such as a shot or pill) and a more well-described payment vehicle was provided (such as out-of-pocket expense). Third, WTP could be better explained by capturing additional socioeconomic information about participants. For instance, participants with higher income could be willing to pay more for STI avoidance. Future work would benefit by including longer

panels and additional covariates. Fourth, the validity of our scope tests would be improved by randomizing the ordering of the infection severity questions. Finally, this study evaluated a unique and specific subpopulation: justice-involved youth in the South-western US. Results of this study may not be generalizable to lower risk young people or to other regions of the US. Future work should study the impact of behavioral risk reduction interventions on the perceived cost of acquiring an STI in other populations.

Table 3.1. Summary statistics

Variable	Mean	SD
Age	16.07	0.973
Gender (=1 if male)	77%	0.421
Pregnancy	38.2%	0.487
Abortion	6.9%	0.253
Positive STD Test	7.8%	0.270
Ethnicity[a]		
African American	6.9%	0.253
American Indian/Native American	7.8%	0.270
Asian or Pacific Islander	0.5%	0.070
Hispanic-American	71.1%	0.454
White	24.5%	0.431
Other	5.4%	0.226

[a] Participants were allowed to identify as more than one ethnicity.

Table 3.2. Double-bounded Tobit model with random effects error

INCURABLE	0.457
	(0.322)
FATAL	1.647***
	(0.324)
*CURABLE*INTERVENTION*	0.974***
	(0.324)
*INCURABLE*INTERVENTION*	2.120***
	(0.328)
*FATAL*INTERVENTION*	3.024***
	(0.332)
WHITE	1.669**
	(0.664)
GENDER	-0.527
	(0.681)
PREGNANCY	0.278
	(0.591)
ABORTION	1.742**
	(0.711)
STITEST	0.105
	(1.071)
CONSTANT	5.566***
	(0.741)
σ_η	3.728***
	(0.226)
σ_ε	3.113***
	(0.086)
χ^2	124.2
Observations	1,224
Subjects	204

SE in parentheses
*** p<0.01, ** p<0.05, * p<0.

Table 3.3. Median WTP estimates and WTP difference

Median WTP		$WTP_{c,0}$	$WTP_{inc,0}$	$WTP_{f,0}$	$WTP_{c,1}$	$WTP_{inc,1}$	$WTP_{f,1}$
\$331.33 (115.07)	$WTP_{c,0}$						
\$523.26 (181.63)	$WTP_{inc,0}$	\$191.93 (215.01)[a]					
\$1 720.72 (601.12)	$WTP_{f,0}$		\$1 197.46** (627.96)[b]				
\$855.40 (297.59)	$WTP_{c,1}$	\$524.07 (319.06)[e]					
\$2 691.73 (948.32)	$WTP_{inc,1}$		\$2 168.47** (965.56)[f]		\$1 836.33** (993.92)[c]		
\$6 643.15 (2361.59)	$WTP_{f,1}$			\$4 922.43** (2,436.90)[g]		\$3 951.42* (2,544.88)[d]	

Alternative hypotheses for scope tests (one-tailed t-tests): *a)* $WTP_{inc,0} > WTP_{c,0}$, *b)* $WTP_{f,0} > WTP_{inc,0}$, *c)* $WTP_{inc,1} > WTP_{c,1}$, *d)* $WTP_{f,1} > WTP_{inc,1}$.

Alternative hypotheses for intervention effect (two-tailed t-tests): *e)* $WTP_{c,1} \neq WTP_{c,0}$, *f)* $WTP_{inc,1} \neq WTP_{inc,0}$, *g)* $WTP_{f,1} \neq WTP_{f,0}$.

SE in parentheses

***p<0.01, **p<0.05, *p<0.1.

Table 3.4. Double-Bounded Tobit Model (pre- and post-intervention)

	Pre-Intervention	Post-Intervention
INCURABLE	0.438	1.218**
	(0.446)	(0.541)
FATAL	1.620***	2.227***
	(0.448)	(0.546)
WHITE	1.504***	2.145***
	(0.436)	(0.541)
GENDER	-0.678	-0.375
	(0.447)	(0.543)
PREGNANCY	-0.147	1.012**
	(0.402)	(0.471)
ABORTION	0.856	2.342**
	(0.765)	(1.049)
STITEST	1.080	-1.222
	(0.707)	(0.846)
CONSTANT	5.874***	6.149***
	(0.533)	(0.643)
σ	4.412***	5.273***
	(0.157)	(0.206)
χ^2	32.85	44.99
Observations	612	612
Subjects	204	204

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.5. Double bounded Tobit model with random effects error (estimating treatment for each STI separately)

	Curable	Incurable	Fatal
INTERVENTION	0.936**	1.691***	1.426***
	(0.377)	(0.373)	(0.358)
WHITE	1.234*	1.593**	2.572***
	(0.636)	(0.719)	(0.758)
GENDER	-0.220	-0.987	-0.295
	(0.651)	(0.736)	(0.766)
ABORTION	0.647	1.817*	2.033*
	(1.033)	(1.096)	(1.121)
PREGNANCY	0.281	0.457	0.267
	(0.571)	(0.644)	(0.670)
STITEST	0.026	0.151	-0.057
	(1.026)	(1.158)	(1.200)
CONSTANT	5.534***	6.314***	6.834***
	(0.705)	(0.789)	(0.819)
σ_η	2.691***	3.377***	3.678***
	(0.308)	(0.306)	(0.308)
σ_ε	3.674***	3.554***	3.333***
	(0.212)	(0.215)	(0.210)
χ^2	76.15	121.7	142.3
Observations	408	408	408
Subjects	204	204	204

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Chapter 4: An Economic Analysis of Project GOAL—A Risk Reduction Intervention for Urban Substance Using MSM

4.1 Introduction

The CDC estimates that there are 20 million new sexually transmitted infections (STIs) each year in the United States, with the direct economic cost of treating these infections estimated to be nearly 16 billion dollars (CDC, 2013). Moreover STIs have an impact on a large proportion of the US population, as an estimated one in three Americans will contract a sexually transmitted infection at some point in their lives (Summers et al., 2002). The burden of these infections is considerably higher in in men who have sex with men (MSM) populations, especially in regard to HIV. For instance, while this population is estimated to represent only 2% of the US population the CDC estimates that male-to-male sexual contact accounts for over 65% of new infections in the United States (CDC, 2015). Additionally, the use of alcohol and drugs has been linked to sexual risk taking behavior and higher STI incidence and prevalence (Carey et al., 2009; Meader et al., 2013; Owusu-Edusei Jr et al., 2013). It follows that the substance-using MSM are among the groups most at-risk for HIV infections in the United States (Carey et al., 2009; Chesney, Barrett, & Stall, 1998; Plankey et al., 2007; Stall & Purcell, 2000).

To mitigate the burden of STIs, a number of interventions have been found to be clinically effective in both heterosexual (Bryan et al., 2009; DiClemente et al., 2004) and MSM populations (Kurtz et al., 2013). Additionally, research has found that substance abuse intervention in conjunction with STI reduction strategies to be clinically valuable

(Mansergh et al., 2010; Shoptaw et al., 2005; Stall, Paul, Barrett, Crosby, & Bein, 1999). However, in addition to clinical outcomes, social planners are becoming increasingly interested in analysis from an economic perspective. As societal resources are limited, economic analysis allows policy makers to maximize the impact of these resources (i.e. spend money as efficiently as possible) both in terms of comparing alternative STI reduction interventions alongside other socially beneficial programs.

From this perspective, a number of sexual risk reduction intervention programs have been found to be valuable (Chesson, Greenberg, & Hennessy, 2002; Pinkerton, Holtgrave, & Jemmott, 2000; Sweat, O'Donnell, & O'Donnell, 2001). However, the economic impact of sexual risk reduction interventions is still not well-known. Considering the large number of at-risk populations and potential intervention strategies, only a small subset have been evaluated from an economic perspecitve. Moreover, as more is learned about transmission dynamics and the medical cost of treating infections, economic estimates must be updated. A specific population that deserves more attention is the substance-using MSM population, as there is a lack of economic evaluations for interventions designed for this population.

In this study we evaluate the economic impact of two separate interventions delivered to substance using MSM: a brief, single-session standard-of-care intervention based on empowerment theory, and an enhanced efficacious multiple-group-session intervention called Project GOAL (Getting Out and Living). A previous study investigated the clinical efficacy of both interventions (Kurtz et al., 2013). This study extends this research to evaluate the economic impacts generated by these interventions. Bernoulli probability models utilizing multiple STI cites and transmission dynamics for

multiple periods are used to estimate the averted infections attributable to each intervention which are then monetized and compared against the implementation costs.

4.2 Background

4.2.1 Economic Analysis of Interventions for Risky Sexual Behavior

To prevent STI acquisition and retransmission, a number of interventions have been designed, which can generally be broken down into two categories, biomedical interventions and behavioral interventions. The objective of biomedical interventions is to screen for and treat infections in a target population. Thus, by reducing the population prevalence, fewer infections will be acquired and retransmitted. Alternatively, the objective of behavioral interventions is to educate individuals about safer methods to have sex, to provide information about the costs associated with acquiring infections, and/or increase the self-efficacy, personal control, and/or coping abilities of participants (otherwise called empowerment). Thus, by changing the behavior of participants, fewer infections will be acquired and retransmitted.

A number of studies have evaluated STI reduction interventions from an economic perspective, generally finding these interventions to be beneficial. For instance, STI interventions have been found to be cost-effective (Chesson et al., 2002; Holtgrave & Kelly, 1996; Pinkerton, Holtgrave, et al., 2000; Sweat et al., 2001). A few studies have found STI interventions to be valuable from a societal perspective (Dealy et al., 2013; Wang et al., 2000). Also, a number of studies have found strategies to combat HIV cost-

effective in developing countries (Creese, Floyd, Alban, & Guinness, 2002; Hogan, Baltussen, Hayashi, Lauer, & Salomon, 2005).

An important difference between biomedical interventions and behavioral interventions is that because behavioral interventions change behavior, they will affect a larger number of STI categories (i.e. infections that are not treatable using medication). For instance, when Dealy et al. (2013) incorporated incurable viral infections into the economic model, the per participant averted direct medical costs increased from $250.41 to $322.33.

Behavioral interventions for risky sexual behavior have an especially high potential for generating economic benefit among the population of substance abusing men who have sex with men (MSM) populations. Moreover, substance abusing MSM are among the highest risk for HIV infections in the United States. A few studies have found positive results of behavioral interventions for risky sexual behavior in MSM populations. For instance, Pinkerton, Holtgrave, and Valdiserri (1997) found HIV-prevention skills training for MSM to provide cost-savings. Pinkerton, Holtgrave, DiFranceisco, Stevenson, and Kelly (1998) found that the reductions in direct medical costs attributable to a community-level risk reduction intervention in gay bars more than offset the costs of intervention costs. Holtgrave and Kelly (1997) found that a behavioral-cognitive group intervention for gay men resulted in cost-savings and Tao and Remafedi (1998) found HIV prevention intervention for gay and bisexual male adolescents in Minnesota to be cost-effective. Additionally, Kahn, Kegeles, Hays, and Beltzer (2001) found a community-level intervention for young gay men to be cost-effective.

4.3 Materials and Methods

4.3.1 Participants

Between November 2008 and October 2010, 515 participants were recruited for the study. Men between the ages of 18 and 55 who met risky-sex and substance abuse criteria were eligible for the study. Specifically, participants' recent sexual history (last 90 days) must have included anal sex with multiple partners and include at least one unprotected anal intercourse event with a non-monogamous partner. The substance abuse criteria required that they engaged in three or more instances of binge drinking or drug use (excluding marijuana) in the last month. Participants who used marijuana were eligible if they used at least 20 times in the last month. Of the original 515 participants our analysis is restricted to the participants who answered all three follow-up risky sexual behavior questions (3, 6 and 12 months), which resulted in a final sample of 420 participants. The potential impact of this sample restriction is explored in the sensitivity analysis.

4.3.2 Procedure

4.3.2.1 Interventions

Participants were randomized into two intervention conditions: (1) an enhanced efficacious HIV risk-reduction counseling condition (standard-of-care) (Kamb et al., 1998), and (2) Project GOAL, a novel small group sexual and substance use risk

intervention based on psychological empowerment theory (Zimmerman, Rappaport, & Seidman, 2000). More details on the interventions can be found in Kurtz et al. (2013).

4.3.2.2 Measures

A particularly advantageous aspect of this trial is the level of detail collected on participants' risky sexual behavior. Specifically, questions were asked about two main types of sex acts (oral and anal), and these questions were conditioned on a number of key variables: (1) number of partners, (2) whether the activity was with their primary partner, (3) whether the act was insertive or receptive, and (4) whether or not a condom was used. For instance, two specific question asked regarding non-primary partner sex were: (1) "In the past 3 months how many times in total did you have receptive anal sex?" and (2) "Of the men that you had receptive anal sex with, how many men was it without a condom?" All of these questions were collected at baseline, three months, six months, and twelve months after the intervention. Questions regarding sexual activities covered the last 90 days. Consequently, information on sexual activities between six months and nine months, post-intervention are not observed.

4.4 Results

4.4.1 Analysis Plan

In this section we provide the methods used to evaluate the economic impact of Project GOAL and the standard intervention. First, a Bernoulli probability model is used to translate self-reported risky sexual behavior into expected STI for each intervention group. Averted infection attributable to the intervention are calculated as the difference in expected STI, assuming that pre-intervention behavior would be maintained in the absence of the program. Next, these averted infections are monetized using expected lifetime direct medical costs of STI treatment that were obtained from the literature. Monetized economic benefits are then compared with the estimated intervention costs. Finally, sensitivity analysis is conducted on a number of imputed prevalence and transmission parameters, in addition to model assumptions.

4.4.1.1 Cost Estimation Procedures

Participants in both intervention conditions were provided HIV tests at the baseline and each follow-up. It is assumed that in practice, interventions will be conducted in a community-based organization which serves the MSM population and that intervention staff members will be comprised of nurses, social workers, or counselors. Training is assumed to be conducted by clinical psychologists. Overhead is assumed to cost 25% of labor and materials.

The enhanced intervention included a single, individual session which required one staff member and lasted approximately 30-45 minutes. Project GOAL was comprised of four, two-hour group sessions attended by five to ten participants. The group sessions required two staff members. In addition to the four group sessions, the enhanced

intervention also included an hour-long individual session with a single staff member. In addition to the time required to deliver the intervention, both interventions required that interventionists receive training.

4.4.1.2 Bernoulli Probability Model

To link self-reported sexual behavior to STI acquisition and retransmission probabilities a Bernoulli probability model similar to Dealy et al. (2013) and Benotsch, Mikytuck, Ragsdale, and Pinkerton (2006) is utilized. An advantage of this methodology is that it is able to predict both the probability that a participant will acquire an infection (known as primary infections) and the probability that a participant will retransmit an infection to a sexual partner (known as secondary infections).

As mentioned previously, this particular study is unique due to the amount of information collected on participants' sexual acts. Including this information involves a slightly more complicated version of the Bernoulli model. The study collected information regarding participants' sexual acts (oral and anal), as well as the role of the participant in each act (insertive or receptive). Overall, these acts represent contact between participants and their partners at three separate body sites (oral/pharynx, anal/rectal and penile/urethral). In order to effectively utilize the information collected during the clinical trial, the Bernoulli model accounts for the participants' sexual activities, role, as well as variation in prevalence at each body site.

Although a participant can acquire an infection at any of three body sites, we assume that treatment costs incurred are the same regardless of the site of the initial

infection and the probability of requiring treatment at any site is bound between 0 and 1. Based on participants' reported sexual activity, we estimate the probability of STI j at each site as

$$P_{i,j} = \left(1-\pi_{i,j}\right)\left\{1-\prod_{l}\left[\left(1-\pi_{l,j}\right)+\pi_{l,j}\left(1-\alpha_{i,l,j}\right)^{n_{i,l}}\left(1-\alpha_{i,l,j}\left(1-\beta\right)\right)^{k_{i,l}}\right]^{m_{i,l}}\right\} \quad (4.1)$$

where i represents the site-of-contact for the intervention participant, and l represents the site-of-contact for their sexual partner ($i,l \in \{\text{pharyngeal, urethral, rectal}\}$). Prevalence is denoted as π, where the term $\pi_{l,j}$ is the probability that a partner is infected with STI j at site l, and the term $\left(1-\pi_{i,j}\right)$ represents the probability that a participant is not infected with (and therefore susceptible to) STI j at corresponding site-of-contact i. The per-act transmission probability for STI j is indicated by $\alpha_{i,l,j}$. Note that the site-of-contact for the participant and their partner jointly determine the act (oral or anal) and the role (insertive or receptive). For example, the combination of $i =$ urethral and $l =$ rectal represents insertive anal sex. In terms of other model parameters, the number of unprotected acts is denoted as $n_{i,l}$ and the number of protected acts (where a condom is used) is denoted as $k_{i,l}$.The number of sexual partners with whom a particular act is engaged is denoted as $m_{i,l}$. Note that transmission probability is reduced by condom efficiency, β. Pharyngeal and rectal infections are determined by a single sex act (receptive oral and anal sex, respectively). However, urethral infections can be generated by insertive oral and anal sex. The probability of contracting an infection at any site is calculated incorporating the risks of infection at each site.

As viral infections are incurable, the probability of being susceptible to infection in period t is affected by the exposure to risk in period $t-1$. Thus, susceptibility to infection is carried over into later periods. However, bacterial infections are treatable, and it is possible for participants to contract an infection and then be susceptible to another infection. Thus, we model the susceptibility of acquiring a primary infection as returning to $\left(1-\pi_{i,j}\right)$ at the start of each 3-month period.

In addition to the possibility of a sexual act causing an acquisition of a STI, if the participant is infected a sexual act can also transmit an infection to a sexual partner. We refer to these types of infections as secondary infections. Secondary infections are calculated in a fashion similar to primary infections, but must be tailored to account for their partner's role in the act. Similar to primary infections, the probability of any single partner acquiring an infection at any site is bound between zero and one. However, the sum of secondary infections may exceed one, as participants may engage with multiple partners.

$$S_{l,j}=\left(1-\pi_{l,j}\right)\left\{1-\prod_{i}\left[\left(1-\pi_{i,j}\right)+\pi_{i,j}\left(1-\alpha_{l,i,j}\right)^{n_{l,i}}\left(1-\alpha_{l,i,j}\right)^{k_{l,i}}\right]\right\} \qquad (4.2)$$

The average probability of secondary infection is calculated by incorporating the average risk at each site, and then multiplying by the number of partners. Unlike primary infections, the risk of viral infections are not carried over periods. Although this clinical trial collected considerable detail, it was not possible to verify whether partners in period t were the same as those in period $t-1$. Thus, it was not possible to account for partners' previous risk.

Two additional assumptions are generally made when estimating Bernoulli probability models. First, it is assumed that participants are serial monogamists. That is, all acts with a single partner take place prior to engaging in an act with a different partner. Second, it is assumed that there exists zero overlap between participants' partners. Both of these assumptions are evaluated in our sensitivity analysis section.

4.4.1.3 Benefit Estimation

To estimate the number of averted infections produced by each intervention, a pre-post model is used, incorporating the change in risky sexual behavior. Specifically, a separate Bernoulli model is calculated for both primary and secondary infections, for each participant, time period, and STI. The aggregated difference in the predicted pre-post STI incidence is the estimated reduction in STI attributable to the intervention condition. Averted infections are monetized using inflation-adjusted cost estimates from (Owusu-Edusei Jr et al., 2013). Details on the cost estimation calculations can be found in the original study (H. W. Chesson et al., 2004)

4.4.1.4 Sensitivity Analysis

To evaluate the robustness of the results, sensitivity analysis is performed on the imputed prevalence rates, transmission probabilities, and treatment costs. This approach is similar to the methods used by Adams, Turner, and Edmunds (2007), van Valkengoed et al. (2001), and Dealy et al. (2013). Specifically, for each of these variables, two additional Bernoulli models are estimated, each with an imputed model parameter

increased (or decreased). Additionally, sensitivity analysis is used to evaluate how modelling assumptions may have influenced the findings. Specifically, assumptions about serial monogamy, and that there is zero overlap between the partners of intervention participants is evaluated. Additionally, we evaluate the impact of excluding participants who failed to return for clinical trial follow-up interviews, and the assumption of zero uptake of PrEP drugs by participants.

Recall that the Bernoulli model used in the primary analysis assumes that participants engage in serial monogamy. That is, all acts with one partner take place before engaging with any acts with a different partner. To evaluate the impact of this assumption, we calculate an alternative Bernoulli model which assumes serial promiscuity. Additionally, the primary analysis assumes that there exists zero overlap between the partners of study participants, meaning that no intervention participant engages in sexual activities with another intervention participant, and no participants engage in sexual activities with the same partner outside of the intervention. Instead if study participants engage in sexual acts with other intervention participants, or if two or more intervention participants share at least one common partner outside of the intervention, secondary infections may be overestimated. To evaluate the impact of this assumption, an alternative extreme assumption would be that there exists 100% overlap, which is equivalent to assuming that all the partners of study participants are themselves study participants. Thus, assuming 100% overlap is equivalent to excluding all secondary infections because these would already be calculated as primary infections.

Another potential limitation of the main Bernoulli model, is that clinical trial recruited 515 participants, of which approximately 18.4% (n=95) of the participants

receiving one of the intervention conditions failed to return for at least one of the clinical trial follow-up interviews. The primary analysis excludes these individuals from the economic benefit calculations. If attrition in the clinical trial was random, then our results would not be biased. However, if, for example, attrition was more likely among individuals for whom the intervention was less-effective, then the benefits calculated by the Bernoulli model could be inflated. In order to test whether attrition in the clinical trial is driving the economic benefits calculated in the primary analysis, an auxiliary Bernoulli model is calculated where risky sexual behavior from missing periods is imputed using data from other reported follow-up behavior. Specifically, this auxiliary Bernoulli model includes all participants regardless of whether they missed a follow-up interview. However, if a missed a follow-up interview, resulting in no data on their behaviors reported for that time period, the participant's baseline behaviors were imputed into the model.

A final limitation of the standard Bernoulli model, which is particularly relevant for risky sexual behavior interventions for MSM populations, is that economic studies generally do not consider medication that can be used to reduce transmission probabilities for HIV. Preexposure prophylaxis (PrEP) has been found to be a highly-effective method for primary prevention of HIV (Smith, Herbst, & Rose, 2015). The primary analysis assumes that there is zero uptake of PrEP in the population. However, if participants in either Project GOAL or the enhanced intervention were taking PrEP, then it would influence the transmission rate of HIV for these individuals. Thus, the probability of primary and secondary HIV infections at baseline and all follow-up periods could be inflated, and therefore, reductions in risk attributable to the interventions could be

inflated. However, the uptake of PrEP in substance using MSM populations is largely unknown. Thus, to evaluate the impact of potential for uptake of PrEP drugs on the Bernoulli model results, we simulates the effect of increased PrEP uptake in the population. Specifically, for a given percentage (from 0% to 100%) participants are chosen randomly and then "treated" with PrEP. The HIV transmission rate for all acts for the participants randomly "treated" with PrEP is reduced by 75.2%, an estimate by Smith et al. (2015). Each PrEP simulation is repeated 300 times in order to minimize the potential for idiosyncratic differences in individual participants' behavior to influence the results.

4.4.2 Outcome Analysis

4.4.2.1 Sample Characteristics

Sample characteristics of the 420 participants who reported to the 12-month follow-up are shown in Table 4.1. 201 participants were randomly assigned into Project GOAL and 231 were assigned to the enhanced intervention. The samples were very similar in terms of age, race, sexual identity, and HIV positive status.

4.4.2.2 Program Costs

Annual and per-participant costs for the implementation of the Project GOAL and the enhanced intervention are presented in Table 4.2. Each intervention condition is assumed to treat 250 participants each year. During the clinical trial, the enhanced intervention utilizes a single, individual session which required one staff member and

lasted approximately 30-45 minutes. Here, it is assumed that each session will last for 45 minutes, requiring 187.5 hours annually. During the clinical trial, Project GOAL was comprised of four group sessions lasting approximately two hours. Each group session was attended by five to ten participants and required two interventionists. Additionally, each Project GOAL participant attended an individual session lasting one hour with a single interventionist. Here, it is assumed that each intervention group will include five participants, and each group will require 21 hours of interventionist labor. Thus, the annual labor required for a Project GOAL program intervention treating 250 participants is 1,050. In addition to ongoing labor required to deliver the intervention, it is assumed that both intervention conditions require annual training. The field staff conducting the interventions for the clinical trials attended 20 hours. It is assumed that each intervention condition will train two interventionists each year and the labor for the interventionist and the trainer is included in the program implementation costs.

For both the standard, and the enhanced intervention, labor costs for interventionists and HIV tests comprise the largest segment of costs associated with the intervention, accounting for approximately 75% of program costs. In order to estimate the cost of intervention implementation, a number of assumptions are made. In particular, it is assumed that each intervention would treat. Including labor, overhead and HIV testing costs, the enhanced intervention would cost approximately $39,126 annually, translating to $156.50 per participant. Implementation of Project GOAL would cost approximately $60,915 annually, translating to $239.12 per participant.

4.4.2.3 Economic Benefits

Recall that in this study, more detailed questions about risky sexual behavior were elicited than other economic studies utilizing the Bernoulli probability model. To utilize this greater level of detail, prevalence rates were obtained for each STI, at each of the three body sites at which an infection may occur (Rectal, Urethral, and Pharyngeal). Additionally, role- and act-dependent transmission probabilities were obtained for each STI (insertive anal, receptive anal, insertive oral and receptive oral). Transmission and prevalence rates were selected from a number of previously published studies to best reflect the characteristics of the intervention participants.

Table 4.3 provides the imputed prevalence rates, transmission probabilities and direct medical treatment costs used in our analysis (Balaji et al., 2013; Beachler et al., 2012; Bohl et al., 2011; Boily et al., 2009; Burchell, Winer, de Sanjose, & Franco, 2006; Hooper et al., 1978; Jones & Wasserheit, 1991; Kent et al., 2005; Machalek, Grulich, Jin, Templeton, & Poynten, 2012; Owusu-Edusei Jr et al., 2013; Platt, Rice, & Mccormack, 1983; Schiffer, Mayer, Fong, Swan, & Wald, 2014). Each transmission probability given in Table 4.3 represents act- and role-specific, per-coital-act probability of transmission with an infected partner. Data was not available for the transmission rates for all sexual act and STI combinations. In these cases transmission rates were estimated using the method suggested by Varghese, Maher, Peterman, Branson, and Steketee (2002), which calculates relative transmission probabilities based on transmission probabilities from known STIs.

Intervention participants' sexual risk behaviors are summarized in Table 4.4. Note that for both the standard intervention and the enhanced intervention, participants reported fewer partners and acts for all sexual activities. Of particular importance is the

reduction in the highest risk sexual activities: unprotected anal sex. Participants in both intervention conditions reported reduced high risk sexual acts, defined as unprotected anal intercourse.

Table 4.5 presents the reduction in risky sexual activities translate to averted infections estimated by the Bernoulli model. Primary infections averted attributable to Project GOAL include: 20.4 Chlamydia infections, 19.3 Gonorrhea infections, 0.59 HIV infections, 8 HPV infections, and 14.5 HSV2 infections. Similarly, primary infections averted amongst the enhanced intervention participants include: 22.4 Chlamydia infections, 18.7 Gonorrhea infections, 0.03 HIV infections, 6.4 HPV infections, and 13 HSV-2 infections. Note that over time, the number of averted primary HIV infections attributable to the enhanced intervention decreases, while the number of averted primary HIV infections attributable to Project GOAL is increasing.

Secondary infections averted amongst the Project GOAL participants include: 273.8 Chlamydia infections, 271.3 Gonorrhea infections, 7 HIV infections, 178.2 HPV infections and 57.6 HSV-2 infections. Secondary infections averted amongst the enhanced intervention participants include: 317.6 Chlamydia infections, 317.1 Gonorrhea infections, 9.3 HIV infections, 202.2 HPV infections, and 60.7 HSV-2 infections. It should be noted that these results are generated assuming that there is zero overlap between participants' partners in either intervention group or even for the same participant across time. As such, secondary infections are potentially inflated. The impact of this assumption on the findings presented in this study is explored further in the sensitivity analysis.

Overall, averted infections for Project GOAL participants translate to a reduction of over $2.5 million in expected direct medical costs (~$12k per participant). Averted infections in the enhanced intervention group translate to a reduction of over $3 million in expected direct medical costs (~$14.1k per participant). Note that averted secondary infections comprise approximately 92% of the benefits generated by Project GOAL, and over 99% of the benefits generated by the enhanced intervention condition.

4.4.2.4 Sensitivity Analysis

Sensitivity analysis results are presented in Table 4.6. Recall that the sensitivity analysis evaluates the sensitivity of the economic impacts to imputed prevalence rates, transmission probabilities, treatment costs, as well as model assumptions.

First, we find that in both interventions, our results are robust to changes in the imputed model parameters. Univariate changes of the prevalence, transmission rate and direct medical costs all produce economic benefits exceeding the implementation of the programs. Additionally, the economic impacts are robust to multivariate changes in imputed model parameters. Joint reductions across imputed model parameters failed to reduce the level of economic benefits of either intervention below the cost of implementation.

Next, we consider changes to modelling assumptions. Recall that the baseline assumption is that there exists zero overlap of partners between participants. If this were not the case, and some participants had common partners, then our estimates of secondary infections would be inflated. At the extreme, there would be 100% overlap, and each participant partner would also be an intervention participant. In this case, it

would be appropriate to exclude secondary infections. For Project GOAL, assuming 100% overlap would reduce economic benefits to approximately $203k (~$4.24 for every $1 spent on implementation). For the enhanced intervention, 100% overlap corresponds to approximately $22.8k in economic benefits (~$0.67 per dollar spent on implementation). Thus, while the economic benefits of Project GOAL are robust to potential overlap in partners, the enhanced intervention is not. Although both of the estimates presented in the sensitivity analysis are extreme assumptions, it is possible to vary the level of overlap between 0% and 100%. Figure 4-1 displays the ratio of averted direct medical costs to program implementation costs as a function of partner overlap. The short-dash line essentially represents the break-even point for the interventions. Note that for the enhanced intervention, the averted medical expenditures exceed implementation costs until overlap exceeds well over 90%.

Relaxing the assumption of serial monogamy increases the ratio of averted direct medical expenditures to implementation costs of the Project GOAL intervention (the range is from $52.70 to $115.41). Similarly, for the enhanced intervention, relaxing the serial monogamy assumptions increases the ratio of averted medical costs to implementation costs (the range is $90.20-$207.52). As expected, the assumption of serial monogamy serves as a conservative estimate of the economic benefits.

Recall that for our primary Bernoulli model, only intervention participants from the clinical trial who show up for each follow-up are included. As attrition may not be random, it is prudent to consider how it may influence the results. To test whether this may be the case, individuals who failed to show up to a follow-up were included, and it is assumed that their behavior reverts back to their behavior reported at the baseline. The

ratio of averted direct medical costs to program implementation costs for Project GOAL were reduced (the range is from $52.70 to $45.27). Similarly, the ratio of averted direct medical costs to program implementation for the enhanced intervention were reduced (the range is $90.20 to $85.38). Overall, even assuming that participants which left the clinical trial reverted back to their pre-intervention risk levels, both interventions produced benefits which exceeded the implementation costs.

In order to test the sensitivity of the Bernoulli model economic benefit calculations to increased uptake of PrEP, this study simulates the effect of uptake in the intervention participants. If 10% of the Project GOAL participants receive PrEP, averted medical costs are approximately $2.35 million (~$50 per dollar spent on implementation). If 50% of the Project GOAL participants receive PrEP, averted medical costs are approximately $1.62 million (~$33.73 per dollar spent on implementation). If 10% of the enhanced intervention participants receive PrEP, averted medical attributable to the intervention are approximately $2.86 million (~$83.74 per dollar spent on implementation). If PrEP uptake increases to 50%, the enhanced intervention produces $1.97 million in averted medical costs (~$57.76 per dollar spent on implementation). Figure 4-2 illustrates the effect of PrEP uptake in the population between 1% and 100%. Although the potential for PrEP to reduce the marginal benefit of subsequent interventions is clear, even at 100% uptake these interventions produce averted medical benefits that greatly exceed the cost of implementation. Thus, even in a population with unrealistically high level of PrEP uptake, these behavioral interventions are beneficial.

4.5 Discussion

This study economically evaluated Project GOAL, a behavioral sexual-risk and drug abuse intervention for MSM. Using our standard model assumptions, the Project GOAL intervention produced approximately $12,601 in averted direct medical expenditures per participant. The enhanced efficacy intervention slightly outperformed Project GOAL, producing approximately $14,080 in averted direct medical expenditures. Implementation costs for Project GOAL were approximately $239 per participant, which translates to approximately $52.70 in averted medical expenditures per $1 spent on implementation. The implementation costs for the standard intervention were approximately $157 per participant, which translates to approximately $90.20 in averted medical expenditures per $1 spent on implementation. Thus, both types of interventions are associated substantial reductions in direct medical costs associated with STIs. Also, both interventions were found to have considerably low program costs that avoided medical costs. Additionally, no economic evidence is found that Project GOAL is beneficial compared with the standard-of-care intervention. These findings contribute to the existing literature evaluating behavioral sexual risk reductions for MSM which have been found to be beneficial social programs (Holtgrave & Kelly, 1997; Pinkerton et al., 1998; Pinkerton et al., 1997; Tao & Remafedi, 1998).

While the additional resources required for implementation of Project GOAL do not appear to yield higher benefits, this could change if the study period were extended. Averted HIV infections attributable to the enhanced intervention reduced gradually over time, while averted infections attributable to Project GOAL increased.

A number of methodological issues should be considered when interpreting our results. First, the standard Bernoulli model has a number of limitations (Pinkerton & Abramson, 1998; Pinkerton, Chesson, Holtgrave, Kassler, & Layde, 2000). In this case, the pre-post model assumes that, in the absence of the program, participants would have continued to exhibit sexual behavior consistent with baseline self-reported behaviors. Also, the model utilized for this study only considered how sexual acts and role affected transmission efficiencies. The epidemiological literature has suggested a number of additional factors that could impact STI transmission efficiency, including age, viral load, preexisting immunological deficiencies, and nutrition, among others (Burchell et al., 2006).

There are additional factors to consider that are specific to the viral STIs. First, the model does not account for the possibility that participants' have received an HPV vaccination. Second, it could be argued that for a highly sexually active group such as the population studied here, averted incurable infections are not necessarily prevented, but rather delayed. However, additional days of relatively better health are valuable. Nonetheless, future research is needed to study the economic consequences of averted viral infections (Kahn et al., 2001).

In summary, the Bernoulli model estimated in this paper presents short-term evidence that both interventions are beneficial social programs. Regardless of model parameters or assumptions the expected direct medical costs averted by participation in the interventions more than offset the cost of the intervention.

Table 4.1. Summary Statistics

	Standard	Project GOAL	Total
Participants	219	201	420
Age	39.0	40.0	39.72
Hispanic	21.6%	28.9%	24.8%
Race			
African American, Black or Caribbean	21.5%	18.4%	20.0%
White	52.1%	46.8%	49.5%
Other	5.9%	5.5%	5.7%
Percent HIV Positive			
Baseline	48.4%	45.3%	46.9%
3-Month	50.2%	45.8%	48.1%
6-Month	50.2%	46.3%	48.3%
12-Month	50.2%	46.3%	48.3%
Sexual Identity			
Gay	83.1%	82.6%	82.9%
Bisexual	15.5%	16.4%	16.0%

Table 4.2. Program Costs

Component	Unit Cost	Annual Quantity	Annual Cost	Cost Per Participant
Project GOAL				
Intervention Costs				
Interventionist Hours	20.21	1,050	$21,221.00	$84.88
HIV Test	26.00	1,000	$26,000.00	$104.00
Annual Training				
Interventionist Hours	20.21	40	$808.40	$1.29
Trainer Hours	35.14	20	$702.80	$1.12
Overhead			$12,182.93	$47.82
Total Costs			$60,914.63	$239.12
Enhanced Standard				
Intervention Costs				
Interventionist Hours	$20.21	187.5	$3,789.38	$15.16
HIV Test	$26.00	1,000	$26,000.00	$104.00
Annual Training				
Interventionist Hours	$20.21	40	$808.40	$3.23
Trainer Hours	$35.14	20	$702.80	$2.81
Overhead			$7,825.14	$31.30
Total Costs			$39,125.72	$156.50

Table 4.3. Bernoulli model population parameters

	Chlamydia	Gonorrhea	HSV-2	HPV	HIV
STI Direct Medical Treatment Costs[m]	$31.59	$83.18	$801.27	$47.38	$320,612
STI population prevalence rates (π)					
Rectal	0.535[a]	0.210[a]	0.261[e]	0.640[c]	0.105[d]
Urethral	0.292[a]	0.149[a]	0.261[e]	0.261[c]	0.105[d]
Pharyngeal	0.066[a]	0.364[a]	0.261[e]	0.280[b]	0.105[d]
Single sex act transmission probabilities (α)					
Insertive Anal	0.0585[i]	0.0689[j]	0.017[h]	0.052[l]	0.00182[g]
Receptive Anal	0.4500[i]	0.5300[k]	0.017[h]	0.400[l]	0.01400[g]
Insertive Oral	0.0045[i]	0.0053[j]	0.017[h]	0.004[l]	0.00014[g]
Receptive Oral	0.0090[i]	0.0106[k]	0.017[h]	0.008[l]	0.00028[g]

[a] (Kent et al., 2005). [b] (Beachler et al., 2012). [c] (Machalek et al., 2012). [d] (Balaji et al., 2013). [e] (Bohl et al., 2011). [g] (Boily et al., 2009). [h] (Schiffer et al., 2014). [i] (Jones & Wasserheit, 1991)*. [j] (Hooper et al., 1978)*. [k] (Platt et al., 1983)*. [l] (Burchell et al., 2006). [m] (Owusu-Edusei Jr et al., 2013).

Table 4.4. Intervention participants' sexual risk behaviors

Project GOAL $(n = 201)$	Baseline	3-Month	6-Month	12-Month
Insertive Oral Sex				
Partners	10.85	5.72	6.44	5.63
Acts	25.61	16.24	17.11	15.83
Receptive Oral Sex				
Partners	10.48	5.94	5.18	5.39
Acts	22.80	15.18	15.63	14.49
Insertive Anal Sex				
Partners	6.74	3.09	2.76	2.65
Protected Acts	6.96	4.05	4.59	2.78
Unprotected Acts	8.79	5.55	5.78	6.03
Receptive Anal Sex				
Partners	5.33	2.93	2.30	3.50
Protected	4.06	2.95	2.76	2.10
Unprotected	9.37	5.37	5.07	5.73
Enhanced Intervention $(n = 219)$	Baseline	3-Month	6-Month	12-Month
Insertive Oral Sex				
Partners	12.66	6.45	6.52	5.35
Acts	27.60	19.01	20.73	18.40
Receptive Oral Sex				
Partners	12.55	5.79	5.74	4.70
Acts	25.82	15.78	16.91	15.52
Insertive Anal Sex				
Partners	6.95	3.78	3.11	2.95
Protected Acts	5.81	3.81	4.01	3.93
Unprotected Acts	13.10	8.26	8.14	7.75
Receptive Anal Sex				
Partners	7.48	2.89	3.78	2.32
Protected	3.89	2.01	3.05	2.28
Unprotected	11.70	5.89	6.59	5.47

Table 4.5. Averted infections

		3-Month	6-Month	12-Month	Total	Total Averted (Monetized)	Average Averted (Monetized)
Project GOAL Intervention (n=201)							
Chlamydia	Primary	6.0	6.7	7.8	20.4	$646	$3
	Secondary	83.4	93.6	96.9	273.8	$8,651	$43
Gonorrhea	Primary	5.8	6.5	7.1	19.3	$1,608	$8
	Secondary	82.8	92.5	96.0	271.3	$22,566	$112
HIV	Primary	0.13	0.29	0.59	0.59	$189,674	$944
	Secondary	2.3	2.4	2.3	7.0	$2,243,142	$11,160
HPV	Primary	3.4	5.3	8.0	8.0	$377	$2
	Secondary	53.9	61.1	63.1	178.2	$8,442	$42
HSV2	Primary	6.3	10.9	14.5	14.5	$11,644	$58
	Secondary	17.5	20.7	19.3	57.6	$46,124	$229
Total						$2,532,874	$12,601
Enhanced Intervention (n=219)							
Chlamydia	Primary	8.7	7.0	6.8	22.4	$709	$3
	Secondary	102.9	92.7	122.0	317.6	$10,034	$46
Gonorrhea	Primary	7.3	5.6	5.8	18.7	$1,559	$7
	Secondary	102.8	92.9	121.5	317.1	$26,379	$120
HIV	Primary	0.13	0.10	0.03	0.03	$9,766	$45
	Secondary	2.8	2.8	3.6	9.3	$2,966,208	$13,544
HPV	Primary	4.6	6.2	6.4	6.4	$303	$1
	Secondary	65.9	58.8	77.6	202.2	$9,583	$44
HSV2	Primary	7.1	10.5	13.0	13.0	$10,441	$48
	Secondary	20.2	17.4	23.1	60.7	$48,617	$222
Total						$3,083,597	$14,080

Table 4.6. Sensitivity Analysis

	Averted Medical		Averted Medical / Intervention Costs	
	Enhanced Intervention	Project GOAL	Enhanced Intervention	Project Goal
Prevalence $(0.5\pi - 1.5\pi)$				
Chlamydia	$8,228-$7,593	$7,092-$6,705	$90.13-$90.11	$52.65-$52.64
Gonorrhea	$15,899-$36,119	$13,769-$31,239	$89.85-$90.44	$52.48-$52.85
HIV	$1,580,096-$41,91,084	$1,295,510-$3,418,116	$49.37-$125.75	$29.04-$73.2
HPV	$9,143-$2,496	$7,991-$2,778	$90.18-$89.98	$52.68-$52.57
HSV-2	$37,684-$70,628	$36,596-$69,043	$89.58-$90.54	$52.26-$52.93
All STIs	$1,651,049-$4,307,919	$1360959-$3,527,881	$48.3-$126.01	$28.32-$73.4
Transmission Probability $(0.5\alpha - 1.5\alpha)$				
Chlamydia	$5,854-$14,994	$5,083-$12,914	$90.06-$90.33	$52.61-$52.77
Gonorrhea	$15,310-$38,694	$13,292-$33,361	$89.83-$90.52	$52.47-$52.89
HIV	$1,523,450-$4,391,169	$1,236,755-$3,601,143	$47.71-$131.6	$27.81-$77.01
HPV	$5,354-$13,900	$4,809-$12,297	$90.07-$90.32	$52.62-$52.77
HSV-2	$32,012-$84,665	$32,047-$81,013	$89.41-$90.95	$52.16-$53.18
All STIs	$1,581,979-$4,543,424	$1,291,984-$3,740,728	$46.28-$132.9	$26.88-$77.83
Medical Costs $(50\% - 150\%)$				
Chlamydia	$5,371-$16,114	$4,648-$13,945	$90.04-$90.36	$52.6-$52.8
Gonorrhea	$13,969-$41,907	$12,087-$36,260	$89.79-$90.61	$52.45-$52.95
HIV	$1,487,987-$4,463,961	$1,216,408-$3,649,225	$46.67-$133.73	$27.39-$78.01
HPV	$4,943-$14,828	$4,410-$13,229	$90.06-$90.35	$52.61-$52.79
HSV-2	$29,529-$88,586	$28,884-$86,652	$89.34-$91.06	$52.1-$53.3
All STIs	$1,541,799-$4,625,396	$1,266,437-$3,799,311	$45.1-$135.3	$26.35-$79.05
Model Assumptions				
Overlap Parameter	$22,778-$3,083,597	$203,949-$2,532,874	$0.67-$90.20	$4.24-$52.70
Serial Monogamy	$3,083,597-$7,094,187	$2,532,874-$5,519,595	$90.20-$207.52	$52.70-$115.41
Intervention Attrition	$3,083,597-$3,505,242	$2,532,874-$2,727,673	$90.2-$85.38	$52.70-$45.27
PrEP Uptake (10% to 50%)	$2,862,683-$1,974,727	$2,354,349-$1,621,061	$83.74-$57.76	$48.98-$33.73

Figure 4-1. Overlapping Partners

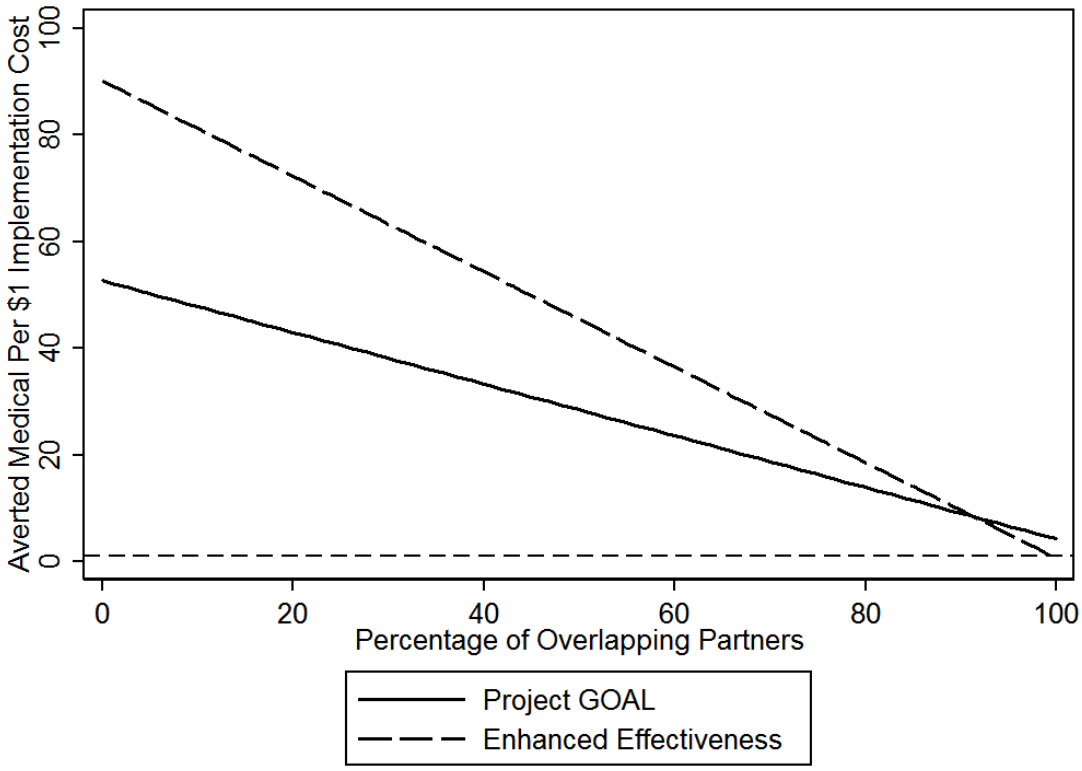
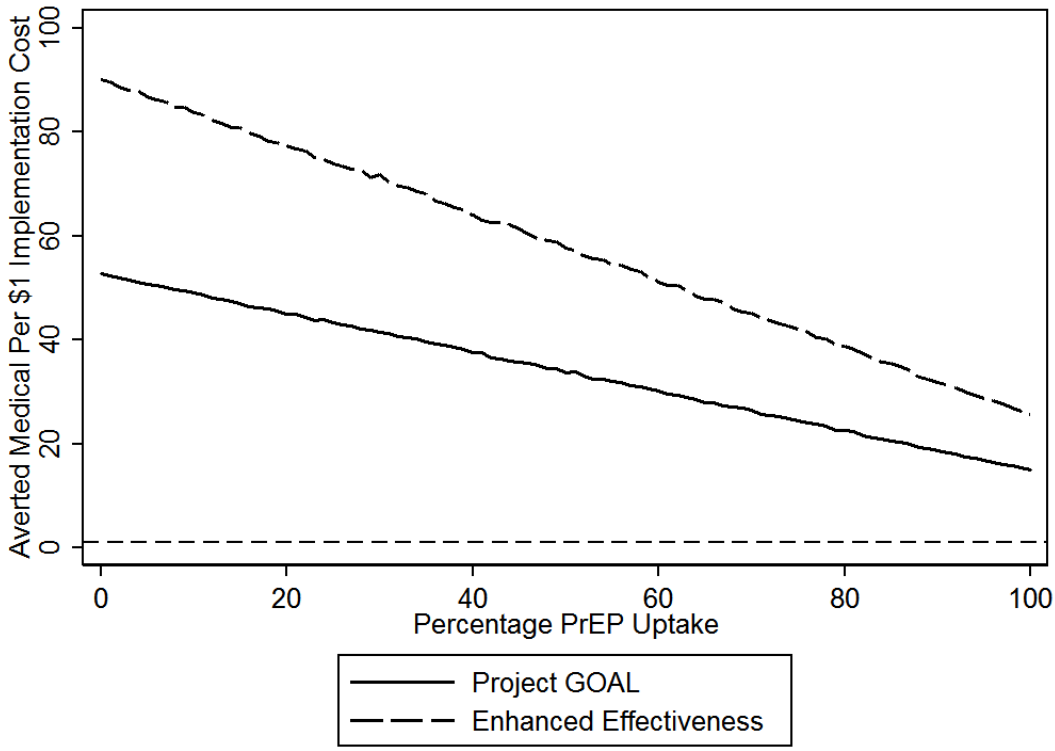


Figure 4-2. PrEP Uptake



Chapter 5: Concluding Remarks

5.1 Dissertation Summaries

This dissertation uses a variety of methods to investigate the costs and consequences associated with risky health behaviors. Each study presented in this dissertation utilizes a different methodology to quantify and monetize consequences associated with risky health behaviors. Of greater interest, perhaps, is how the results of these studies can help to better-understand interventions designed to prevent or mitigate the impacts of risky health behaviors.

Chapter 2 utilizes a hedonic home price model to quantify the negative externality of clandestine lab discovery as well as the positive externality of decontamination. This work can help to better-understand the value of meth lab prevention and remediation. Given the steep cost associated with decontamination (not to mention the administrative costs associated with overseeing meth lab decontamination), this information could be utilized in future cost benefit analyses evaluating mandatory meth lab decontamination. While it seems clear that future occupants of the dwellings used to produce meth are likely to benefit from compulsory decontamination, the findings from Chapter 2 suggest that the benefits associated with decontamination may extend to a number of households in the surrounding area.

Additional work building on the findings presented in chapter 2 could evaluate the impact of meth lab discovery and decontamination in other areas. The social and spatial characteristics of Linn County, Oregon are not representative of the US as a whole.

Future work could focus on urban areas with more diverse population. The benefits of other meth lab policies may also be better-understood using a similar approach. For example, the restrictions placed on meth precursors vary across states. Furthermore, the states which place the greatest restrictions on precursors have reduced meth lab incidence and scale considerably. Theoretically, both of these impacts could be reflected in home prices. Heterogeneous meth precursor restrictions across states may provide a natural experiment in which to study this impact.

The study presented in Chapter 3 utilizes a contingent valuation survey designed to estimate the nonmarket value of STI avoidance. However, the most important discovery from Chapter 3 is that scope sensitivity increased following the intervention. Scope tests are typically used to evaluate the construct validity of a specific survey instrument. In this context, economic rationality is the construct upon which the validity of the survey is evaluated. The increased sensitivity to scope demonstrated by the MARS participants following the intervention suggests that the intervention itself may cause individuals to value STI avoidance in a more rational manner.

The results of the scope tests conducted in Chapter 3 suggest that future work estimating the nonmarket value of STI avoidance could be beneficial to work evaluating the social benefits of similar behavioral interventions. While the unique population evaluated in Chapter 3 may limit the generalizability of the point-estimates from this study, future work utilizing alternative populations could estimate WTP to avoid STIs which may be generalizable to the wider population.

The findings from Chapter 3 also motivate future work reconciling differences in theoretical constructs utilized by psychologists and economists. Specifically, WTP and

the constructs of the Theory of Planned Behavior. Chapter 3 provides evidence that elicited WTP to avoid STIs is: 1) consistent with economic theory, and; 2) affected by the theory-based MARS intervention. The MARS intervention is based on the Theory of Planned Behavior. Previous work has studied the relationship between WTP and the constructs of the Theory of Planned Behavior, finding mixed results (Kahneman & Ritov, 1994; Ryan & Spash, 2011). However, this relationship has not been evaluated in the context of a risky health behavior intervention such as Project MARS, where the intervention is designed to affect TPB constructs.

Chapter 4 uses a Bernoulli probability model to evaluate the economic impact of two behavioral risky-sex interventions. Both interventions generate cost-savings across all reasonable model assumptions. Economic evaluations, such as those presented in Chapter 4 are crucial to identifying efficacious and cost-effective interventions which have the potential to improve health and reduce public health expenditures simultaneously. These interventions are often optimized for efficacy in specific populations which face unique transmission and epidemiological risks. The economic impacts of these interventions will be sensitive to variation in these risks. Thus, in order to justify wide-spread adoption of interventions such as those discussed in Chapter 4 requires robust sensitivity analysis. This work has inspired a number of additional research questions. First, the averted infections calculated by the Bernoulli model presented in Chapter 4 were monetized using medical treatment costs. However, as discussed in Chapter 3, the benefits of the intervention may extend beyond the direct medical costs associated with treatment of STIs. A logical extension of the work presented in Chapter 4 would include the nonmarket value of STI avoidance. Future work

could combine the approaches from Chapter 3 and Chapter 4, using a Bernoulli model to estimate averted infections and then monetizing averted infections using elicited WTP. Another research question would include the emerging threat of the Zika virus. While the epidemiological details of sexual transmission of the Zika virus are still being researched, once contracted, the virus poses a serious threat to fetuses and adults with compromised immune systems (e.g., individuals with HIV/AIDS). Future work could incorporate the risk of Zika, as it represents not only a consequence of risky sexual behavior, but also has an impact on the costs of associated with risky sex consequences.

References

Adams, E. J., Turner, K. M., & Edmunds, W. J. (2007). The cost effectiveness of opportunistic chlamydia screening in England. *Sex Transm Infect, 83*(4), 267-274; discussion 274-265. doi:10.1136/sti.2006.024364

Ajzen, I. (1991). The theory of planned behavior. *Organ Behav Hum Decis Process, 50*(2), 179-211. doi:10.1016/0749-5978(91)90020-t

Armitage, C. J., & Conner, M. (2001). Efficacy of the theory of planned behaviour: A meta-analytic review. *Br J Soc Psychol, 40*(4), 471-499. doi:http://dx.doi.org/10.1348/014466601164939

Awad, I., & Holländer, R. (2010). Applying contingent valuation method to measure the total economic value of domestic water services: a case study in Ramallah Governorate, Palestine. *European Journal of Economics, Finance and Administrative Sciences, 20*, 76-93.

Balaji, A. B., Bowles, K. E., Le, B. C., Paz-Bailey, G., Oster, A. M., & Group, N. S. (2013). High HIV incidence and prevalence and associated factors among young MSM, 2008. *AIDS, 27*(2), 269-278.

Beachler, D. C., Weber, K. M., Margolick, J. B., Strickler, H. D., Cranston, R. D., Burk, R. D., . . . Stammer, E. E. (2012). Risk factors for oral HPV infection among a high prevalence population of HIV-positive and at-risk HIV-negative adults. *Cancer Epidemiology Biomarkers & Prevention, 21*(1), 122-133.

Benotsch, E. G., Mikytuck, J. J., Ragsdale, K., & Pinkerton, S. D. (2006). Sexual risk and HIV acquisition among men who have sex with men travelers to Key West,

Florida: a mathematical modeling analysis. *AIDS Patient Care & STDs, 20*(8), 549-556.

Biglan, A., Ary, D. V., Smolkowski, K., Duncan, T., & Black, C. (2000). A randomised controlled trial of a community intervention to prevent adolescent tobacco use. *Tob Control, 9*(1), 24-32. doi:DOI 10.1136/tc.9.1.24

Bishop, R. C. (2003). Where to from Here? In P. A. Champ, K. J. Boyle, & T. C. Brown (Eds.), *A Primer on nonmarket valuation* (pp. 537-566). Boston, MA: Kluwer Academic Publishers.

Bishop, R. C., Champ, P. A., & Mullarkey, D. J. (1995). Contingent valuation. In D. W. Bromley (Ed.), *Handbook of environmental economics* (pp. 629-654): Blackwell.

Black, S. E. (1999). Do better schools matter? Parental valuation of elementary education. *Quarterly journal of economics*, 577-599.

Bobinac, A., van Exel, J., Rutten, F. F., & Brouwer, W. B. (2014). The value of a QALY: individual willingness to pay for health gains under risk. *Pharmacoeconomics, 32*(1), 75-86. doi:10.1007/s40273-013-0110-1

Bobo, C. (2013). Establishing a Floor: Remediation Requirements for Meth Labs. *Wm. & Mary Envtl. L. & Pol'y Rev., 38*, 507.

Bohl, D. D., Katz, K. A., Bernstein, K., Wong, E., Raymond, H. F., Klausner, J. D., & McFarland, W. (2011). Prevalence and correlates of herpes simplex virus type-2 infection among men who have sex with men, San Francisco, 2008. *Sexually Transmitted Diseases, 38*(7), 617-621.

Boily, M.-C., Baggaley, R. F., Wang, L., Masse, B., White, R. G., Hayes, R. J., & Alary, M. (2009). Heterosexual risk of HIV-1 infection per sexual act: systematic review

and meta-analysis of observational studies. *The Lancet Infectious Diseases, 9*(2), 118-129.

Boyle, K. J. (2003). Contingent Valuation in Practice. In P. A. Champ, K. J. Boyle, & T. C. Brown (Eds.), *A Primer on Nonmarket Valuation* (Vol. 3, pp. 111-169): Kluwer Academic Publishers.

Brouwer, K. C., Case, P., Ramos, R., Magis-Rodriguez, C., Bucardo, J., Patterson, T. L., & Strathdee, S. A. (2006). Trends in production, trafficking, and consumption of methamphetamine and cocaine in Mexico. *Substance use & misuse, 41*(5), 707-727.

Bruvold, W. H. (1993). A meta-analysis of adolescent smoking prevention programs. *Am J Public Health, 83*(6), 872-880.

Bryan, A. D., Schmiege, S. J., & Broaddus, M. R. (2009). HIV risk reduction among detained adolescents: a randomized, controlled trial. *Pediatrics, 124*(6), e1180-1188. doi:10.1542/peds.2009-0679

Burchell, A. N., Winer, R. L., de Sanjose, S., & Franco, E. L. (2006). Chapter 6: Epidemiology and transmission dynamics of genital HPV infection. *Vaccine, 24 Suppl 3*, S3/52-61. doi:10.1016/j.vaccine.2006.05.031

Callahan, T. J., Montanaro, E. A., Magnan, R. E., & Bryan, A. D. (2013). Project MARS: design of a multi-behavior intervention trial for justice-involved youth. *Transl Behav Med*, 1-9. doi:10.1007/s13142-013-0192-5

Callan, A., & O'Shea, E. (2015). Willingness to pay for telecare programmes to support independent living: Results from a contingent valuation study. *Soc Sci Med, 124*, 94-102. doi:10.1016/j.socscimed.2014.11.002

Carey, J. W., Mejia, R., Bingham, T., Ciesielski, C., Gelaude, D., Herbst, J. H., . . . Jenkins, R. A. (2009). Drug use, high-risk sex behaviors, and increased risk for recent HIV infection among men who have sex with men in Chicago and Los Angeles. *AIDS and Behavior, 13*(6), 1084-1096.

Carson, R. T. (1997). Contingent valuation surveys and tests of insensitivity to scope. In R. J. Kopp, W. W. Pommerehne, & N. Schwarz (Eds.), *Determining the Value of Non-marketed Goods: Economic, Pschychological, and Policy Relevant Aspects of Contingent Valuation Methods* (Vol. 10): Springer.

Carson, R. T. (2012). Contingent Valuation: A Practical Alternative when Prices Aren't Available. *J Econ Perspect, 26*(4), 27-42. doi:10.1257/jep.26.4.27

Carson, R. T., & Mitchell, R. C. (1995). Sequencing and nesting in contingent valuation surveys. *J Environ Econ Manage, 28*(2), 155-173. doi:DOI 10.1006/jeem.1995.1011

Cawley, J., & Ruhm, C. (2011). *The economics of risky health behaviors*. Retrieved from

CDC. (2015). Diagnoses of HIV infection in the United States and dependent areas: HIV surveillance report.

Chaloupka, F. J., & Warner, K. E. (2000). The economics of smoking. *Handbook of health economics, 1*, 1539-1627.

Chay, K. Y., & Greenstone, M. (1998). *Does air quality matter? Evidence from the housing market*. Retrieved from

Chesney, M. A., Barrett, D. C., & Stall, R. (1998). Histories of substance use and risk behavior: precursors to HIV seroconversion in homosexual men. *American Journal of Public Health, 88*(1), 113-116.

Chesson, H. W., Blandford, J. M., Gift, T. L., Tao, G., & Irwin, K. L. (2004). The Estimated Direct Medical Cost of Sexually Transmitted Diseases Among American Youth, 2000. *Perspectives on Sexual and Reproductive Health, 36*(1), 11-19. doi:10.1363/3601104

Chesson, H. W., Blandford, J. M., Gift, T. L., Tao, G. Y., & Irwin, K. L. (2004). The estimated direct medical cost of sexually transmitted diseases among American youth, 2000. *Perspect Sex Reprod Health, 36*(1), 11-19. doi:DOI 10.1111/j.1931-2393.2004.tb00003.x

Chesson, H. W., Greenberg, J. B., & Hennessy, M. (2002). The cost-effectiveness of the WINGS intervention: a program to prevent HIV and sexually transmitted diseases among high-risk urban women. *BMC Infectious Diseases, 2*(1), 24. doi:10.1186/1471-2334-2-24

The Combat Methamphetamine Epidemic Act of 2005, Pub. L. No. 109-177 § 701-756, 120 Stat. 192, 256-277 (March 9, 2006).

Congdon-Hohman, J. M. (2013). The lasting effects of crime: The relationship of discovered methamphetamine laboratories and home values. *Regional Science and Urban Economics, 43*(1), 31-41.

Creese, A., Floyd, K., Alban, A., & Guinness, L. (2002). Cost-effectiveness of HIV/AIDS interventions in Africa: a systematic review of the evidence. *The Lancet, 359*(9318), 1635-1642.

Cuijpers, P., Riper, H., & Lemmers, L. (2004). The effects on mortality of brief interventions for problem drinking: a meta-analysis. *Addiction, 99*(7), 839-845. doi:http://www.ncbi.nlm.nih.gov/pubmed/11795063

Cunningham, S., & Finlay, K. (2013). Parental substance use and foster care: Evidence from two methamphetamine supply shocks. *Economic Inquiry, 51*(1), 764-782.

Dallery, J., Silverman, K., Chutuape, M. A., Bigelow, G. E., & Stitzer, M. L. (2001). Voucher-based reinforcement of opiate plus cocaine abstinence in treatment-resistant methadone patients: effects of reinforcer magnitude. *Exp Clin Psychopharmacol, 9*(3), 317-325.

Davis, L. W. (2004). The effect of health risk on housing values: Evidence from a cancer cluster. *American Economic Review, 94*(5), 1693-1704.

Dawe, S., Davis, P., Lapworth, K., & McKetin, R. (2009). Mechanisms underlying aggressive and hostile behavior in amphetamine users. *Current Opinion in Psychiatry, 22*(3), 269-273.

Dealy, B. C., Horn, B. P., Callahan, T. J., & Bryan, A. D. (2013). The economic impact of Project MARS (Motivating Adolescents to Reduce Sexual Risk). *Health Psychol, 32*(9), 1003-1012. doi:10.1037/a0033607

Dewan, S., & Brown, R. (2009). Illnesses afflict homes with a criminal past. *The New York Times*. Retrieved from http://www.nytimes.com/2009/07/14/us/14meth.html?emc=eta1

DiClemente, R. J., Wingood, G. M., Harrington, K. F., Lang, D. L., Davies, S. L., Hook, E. W., 3rd, . . . Robillard, A. (2004). Efficacy of an HIV prevention intervention for African American adolescent girls: a randomized controlled trial. *JAMA, 292*(2), 171-179. doi:10.1001/jama.292.2.171

Dinh-Zarr, T., Diguiseppi, C., Heitman, E., & Roberts, I. (1999). Preventing injuries through interventions for problem drinking: a systematic review of randomized

controlled trials. *Alcohol Alcohol, 34*(4), 609-621. doi:DOI 10.1093/alcalc/34.4.609

Dobkin, C., & Nicosia, N. (2009). The war on drugs: methamphetamine, public health, and crime. *The American Economic Review, 99*(1), 324.

Doyle, S., Lloyd, A., Birt, J., Curtis, B., Ali, S., Godbey, K., . . . Halford, J. C. (2012). Willingness to pay for obesity pharmacotherapy. *Obesity, 20*(10), 2019-2026.

Drug Enforcement Administration. (2015). National Clandestine Laboratory Register - Oregon. http://www.dea.gov/clan-lab/or.pdf

Dunn, K. E., Saulsgiver, K. A., & Sigmon, S. C. (2011). Contingency management for behavior change: Applications to promote brief smoking cessation among opioid-maintained patients. *Exp Clin Psychopharmacol, 19*(1), 20.

Durant, N., Baskin, M. L., Thomas, O., & Allison, D. B. (2008). School-based obesity treatment and prevention programs: all in all, just another brick in the wall? *Int J Obes (Lond), 32*(12), 1747.

Ethridge, D. E. (1992). Characteristic supplies and demands in a hedonic framework: US market for cotton fiber attributes. *American Journal of Agricultural Economics, 74*(4), 991-1002.

Fisher, E. B., Fitzgibbon, M. L., Glasgow, R. E., Haire-Joshu, D., Hayman, L. L., Kaplan, R. M., . . . Ockene, J. K. (2011). Behavior matters. *Am J Prev Med, 40*(5), e15-e30.

Frederick, S., Loewenstein, G., & O'donoghue, T. (2002). Time discounting and time preference: A critical review. *J Econ Lit, 40*(2), 351-401.

Freeman, A. M. (2003). *The measurement of environmental and resource values: theory and methods*: Resources for the Future.

Freeman III, A. M. (1995). Hedonic Pricing Models. In D. W. Bromley (Ed.), *Handbook of environmental economics* (pp. 672-686): Blackwell.

Freeman, P. R., & Talbert, J. (2012). *Impact of State Laws Regulating Pseudoephedrine on Methamphetamine Trafficking and Abuse*. Retrieved from Quincy, MA: http://www.nascsa.org/pdf/nascsapseudoephedrinewhitepaper4.12.pdf

Galárraga, O., Sosa-Rubí, S. G., Infante, C., Gertler, P. J., & Bertozzi, S. M. (2014). Willingness-to-accept reductions in HIV risks: conditional economic incentives in Mexico. *Eur J Health Econ, 15*(1), 41-55.

Gamper-Rabindran, S., & Timmins, C. (2013). Does cleanup of hazardous waste sites raise housing values? Evidence of spatially localized benefits. *Journal of Environmental Economics and Management, 65*(3), 345-360.

Glanz, K., & Bishop, D. B. (2010). The role of behavioral science theory in development and implementation of public health interventions. *Annu Rev Public Health, 31*, 399-418.

Goodwin, H., Holcomb, R. B., & Rister, M. E. (1996). Implicit price estimation of rice quality attributes for asian americans. *Journal of Agricultural and Applied Economics, 28*(02), 291-302.

Graves, P., Murdoch, J. C., Thayer, M. A., & Waldman, D. (1988). The robustness of hedonic price estimation: urban air quality. *Land Economics, 64*(3), 220-233.

Gray, K. M., Carpenter, M. J., Baker, N. L., Hartwell, K. J., Lewis, A. L., Hiott, D. W., . . . Upadhyaya, H. P. (2011). Bupropion SR and contingency management for adolescent smoking cessation. *J Subst Abuse Treat, 40*(1), 77-86.

Greenberg, D., Bakhai, A., Neumann, P. J., & Cohen, D. J. (2004). Willingness to pay for avoiding coronary restenosis and repeat revascularization: results from a contingent valuation study. *Health policy, 70*(2), 207-216. doi:http://dx.doi.org/10.1016/j.healthpol.2004.03.002

Greenfield, T. K., Ye, Y., Kerr, W., Bond, J., Rehm, J., & Giesbrecht, N. (2009). Externalities from alcohol consumption in the 2005 US National Alcohol Survey: implications for policy. *International Journal of Environmental Research and Public Health, 6*(12), 3205-3224.

Gruber, J., & Zinman, J. (2001). Youth smoking in the United States: evidence and implications *Risky behavior among youths: An economic analysis* (pp. 69-120): University of Chicago Press.

Gruenewald, P. J., Ponicki, W. R., Remer, L. G., Waller, L. A., Zhu, L., & Gorman, D. M. (2013). Mapping the spread of methamphetamine abuse in California from 1995 to 2008. *American Journal of Public Health, 103*(7), 1262-1270.

Gupta, I., & Trivedi, M. (2014). Willingness to Pay for Health Insurance Among HIV-Positive Patients in India. *Applied health economics and health policy, 12*(6), 601-610.

Gyrd-Hansen, D., Kjær, T., & Nielsen, J. S. (2012). Scope insensitivity in contingent valuation studies of health care services: should we ask twice? *Health Economics, 21*(2), 101-112.

Haab, T. C., Interis, M. G., Petrolia, D. R., & Whitehead, J. C. (2013). From Hopeless to Curious? Thoughts on Hausman's "Dubious to Hopeless" Critique of Contingent Valuation. *Appl Econ Perspect Policy, 35*(4), 593-612.

Hammitt, J. K., & Graham, J. D. (1999). Willingness to pay for health protection: inadequate sensitivity to probability? *Journal of Risk and Uncertainty, 18*(1), 33-62.

Hanley, N., Ryan, M., & Wright, R. (2003). Estimating the monetary value of health care: lessons from environmental economics. *Health Econ, 12*(1), 3-16.

Hausman, J. (2012). Contingent Valuation: From Dubious to Hopeless. *J Econ Perspect, 26*(4), 43-56.

Hite, D., Chern, W., Hitzhusen, F., & Randall, A. (2001). Property-value impacts of an environmental disamenity: the case of landfills. *The Journal of Real Estate Finance and Economics, 22*(2-3), 185-202.

Hogan, D. R., Baltussen, R., Hayashi, C., Lauer, J. A., & Salomon, J. A. (2005). Cost effectiveness analysis of strategies to combat HIV/AIDS in developing countries. *Bmj, 331*(7530), 1431-1437.

Holtgrave, D. R., & Kelly, J. A. (1996). Preventing HIV/AIDS among high-risk urban women: the cost-effectiveness of a behavioral group intervention. *American Journal of Public Health, 86*(10), 1442-1445. doi:10.2105/ajph.86.10.1442

Holtgrave, D. R., & Kelly, J. A. (1997). Cost-effectiveness of an HIV/AIDS prevention intervention for gay men. *AIDS and Behavior, 1*(3), 173-180.

Hooper, R. R., Reynolds, G. H., Jones, O. G., Zaidi, A., Wiesner, P. J., Latimer, K. P., . . . Holmes, K. K. (1978). Cohort Study of Venereal Disease. I: The Risk of

Gonorrhea Transmission From Infected Woment to Men. *American Journal of Epidemiology, 108*(2), 136-144.

Joint Federal Task Force of the Drug Enforcement Administration, U.S. Environmental Protection Agency, & U.S. Coast Guard. (2005). *Guidelines for Law Enforcement for the Cleanup of Clandestine Drug Laboratories*. Washington, D.C. Retrieved from http://www.justice.gov/dea/resources/img/redbook.pdf.

Jones, R. B., & Wasserheit, J. N. (1991). Introduction to the Biology and Natural History of sexually Transmitted Diseases. In J. N. Wasserheit, S. O. Aral, K. K. Holmes, & P. J. Hitchcock (Eds.), *Research Issues in Human behavior and sexually transmitted diseases in the AIDS era* (pp. 11-37). Washington, D.C.: American Society for Microbiology,.

Jordan, J. L., Shewfelt, R., Prussia, S. E., & Hurst, W. (1985). Estimating implicit marginal prices of quality characteristics of tomatoes. *Southern Journal of Agricultural Economics, 17*(02), 139-146.

Kahn, J. G., Kegeles, S. M., Hays, R., & Beltzer, N. (2001). Cost-effectiveness of the Mpowerment Project, a community-level intervention for young gay men. *J Acquir Immune Defic Syndr, 27*(5), 482-491.

Kahneman, D., & Ritov, I. (1994). Determinants of stated willingness to pay for public goods: A study in the headline method. *Journal of Risk and Uncertainty, 9*(1), 5-37.

Kamb, M. L., Fishbein, M., Douglas Jr, J. M., Rhodes, F., Rogers, J., Bolan, G., . . . Iatesta, M. (1998). Efficacy of risk-reduction counseling to prevent human

immunodeficiency virus and sexually transmitted diseases: a randomized controlled trial. *JAMA, 280*(13), 1161-1167.

Kasunic, A., & Lee, M. A. (2014). Societal burden of substance abuse. *International Public Health Journal, 6*(3), 269.

Kent, C. K., Chaw, J. K., Wong, W., Liska, S., Gibson, S., Hubbard, G., & Klausner, J. D. (2005). Prevalence of rectal, urethral, and pharyngeal chlamydia and gonorrhea detected in 2 clinical settings among men who have sex with men: San Francisco, California, 2003. *Clinical Infectious Diseases, 41*(1), 67-74.

Klick, J., & Stratmann, T. (2003). The effect of abortion legalization on sexual behavior: evidence from sexually transmitted diseases. *J Legal Stud, 32*(2), 407-433.

Klick, J., & Stratmann, T. (2007). Abortion Access and Risky Sex Among Teens: Parental Involvement Laws and Sexually Transmitted Diseases. *J Law Econ Organ, 24*(1), 2-21. doi:10.1093/jleo/ewm041

Kling, C. L., Phaneuf, D. J., & Zhao, J. (2012). From Exxon to BP: has some number become better than no number? *J Econ Perspect, 26*(4), 3-26.

Kurtz, S. P., Stall, R. D., Buttram, M. E., Surratt, H. L., & Chen, M. (2013). A randomized trial of a behavioral intervention for high risk substance-using MSM. *AIDS and Behavior, 17*(9), 2914-2926.

Lee, J. M., Chen, S. H., Liu, H. H., Hung, J. Y., & Huang, M. Y. (2010). Effects of health risk information on addictive goods consumption: A case of tobacco, alcohol, and betel nuts in Taiwan. *Contemp Econ Policy, 28*(3), 406-413.

Levine, P. B. (2001). The sexual activity and birth-control use of American teenagers *Risky behavior among youths: An economic analysis* (pp. 167-218): University of Chicago Press.

Levitt, S. D., & Porter, J. (2001). How dangerous are drinking drivers? *Journal of political Economy, 109*(6), 1198-1237.

Linden, L., & Rockoff, J. E. (2008). Estimates of the impact of crime risk on property values from Megan's laws. *The American Economic Review*, 1103-1127.

Linn County Assessor's Office. Sale Data. Retrieved April 4, 2014 http://www.co.linn.or.us/assessorshomep/sale_csv.htm

Loewenstein, G., Brennan, T., & Volpp, K. G. (2007). Asymmetric paternalism to improve health behaviors. *JAMA, 298*(20), 2415-2417.

Loewenstein, G., & Prelec, D. (1992). Anomalies in intertemporal choice: Evidence and an interpretation. *The Quarterly Journal of Economics*, 573-597.

Machalek, D. A., Grulich, A. E., Jin, F., Templeton, D. J., & Poynten, I. M. (2012). The epidemiology and natural history of anal human papillomavirus infection in men who have sex with men. *Sexual health, 9*(6), 527-537.

Mansergh, G., Koblin, B. A., McKirnan, D. J., Hudson, S. M., Flores, S. A., Wiegand, R. E., . . . Team, P. M. S. (2010). An intervention to reduce HIV risk behavior of substance-using men who have sex with men: a two-group randomized trial with a nonrandomized third group. *PLoS Med, 7*(8), e1000329.

Martínez-Paz, J. M., & Perni, A. (2011). Environmental cost of groundwater: a contingent valuation approach. *Int J Environ Res, 5*(3), 603-612.

McCluskey, J. J., & Rausser, G. C. (2003). Stigmatized asset value: is it temporary or long-term? *Review of Economics and Statistics, 85*(2), 276-285.

McMillan, M. L., Reid, B. G., & Gillen, D. W. (1980). An extension of the hedonic approach for estimating the value of quiet. *Land Economics, 56*(3), 315-328.

Meader, N., Semaan, S., Halton, M., Bhatti, H., Chan, M., Llewellyn, A., & Des Jarlais, D. (2013). An International Systematic Review and Meta-analysis of Multisession Psychosocial Interventions Compared with Educational or Minimal Interventions on the HIV Sex Risk Behaviors of People Who Use Drugs. *AIDS and Behavior*.

Mialon, H. M., Nesson, E. T., & Samuel, M. C. (2014). Crystal Clear? The Relationship Between Methamphetamine Use and Sexually Transmitted Infections. *Health Economics*.

Nicosia, N., Pacula, R. L., Kilmer, B., Lundberg, R., & Chiesa, J. (2009). *The economic cost of methamphetamine use in the United States, 2005*. Retrieved from

Olsen, J. A., Donaldson, C., & Pereira, J. (2004a). The insensitivity of 'willingness-to-pay' to the size of the good: New evidence for health care. *Journal of Economic Psychology, 25*(4), 445-460.

Olsen, J. A., Donaldson, C., & Pereira, J. (2004b). The insensitivity ofwillingness-to-pay'to the size of the good: New evidence for health care. *J Econ Psychol, 25*(4), 445-460.

Olsen, J. A., Røgeberg, O. J., & Stavem, K. (2012). What Explains Willingness to Pay for Smoking-Cessation Treatments—Addiction Level, Quit-Rate Effectiveness or the Opening Bid? *Applied health economics and health policy, 10*(6), 407-415.

Operario, D., Kuo, C., Sosa-Rubí, S. G., & Gálarraga, O. (2013). Conditional economic incentives for reducing HIV risk behaviors: Integration of psychology and behavioral economics. *Health Psychol, 32*(9), 932.

Or. Rev. Stat. Ann. § 453.861, (1989).

Oregon Department of Human Services. (2015). *Clandestine Drug Lab Program Flowchart*. Retrieved from http://public.health.oregon.gov/HealthyEnvironments/HealthyNeighborhoods/ClandestineDrugLabs/Documents/flowchart.pdf.

Owusu-Edusei Jr, K., Chesson, H. W., Gift, T. L., Tao, G., Mahajan, R., Ocfemia, M. C. B., & Kent, C. K. (2013). The Estimated Direct Medical Cost of Selected Sexually Transmitted Infections in the United States, 2008. *Sexually Transmitted Diseases, 40*(3), 197-201.

Pacula, R. L., Grossman, M., Chaloupka, F. J., O'Malley, P. M., Johnston, L., & Farrelly, M. C. (2000). *Marijuana and youth*. Retrieved from

Pinkerton, S. D., & Abramson, P. R. (1998). The Bernoulli-process model of HIV transmission: Applications and implications. In D. R. Holtgrave (Ed.), *Handbook of economic evaluation of HIV prevention programs.* (pp. 13-32). New York, NY US: Plenum Press.

Pinkerton, S. D., Chesson, H. W., Holtgrave, D. R., Kassler, W., & Layde, P. M. (2000). When is an HIV Infection Prevented and when is it Merely Delayed? *Evaluation Review, 24*(3), 251-271. doi:10.1177/0193841x0002400301

Pinkerton, S. D., Holtgrave, D. R., DiFranceisco, W. J., Stevenson, L. Y., & Kelly, J. A. (1998). Cost-effectiveness of a community-level HIV risk reduction intervention.

American Journal of Public Health, 88(8), 1239-1242. doi:10.2105/ajph.88.8.1239

Pinkerton, S. D., Holtgrave, D. R., & Jemmott, J. B., 3rd. (2000). Economic evaluation of HIV risk reduction intervention in African-American male adolescents. *J Acquir Immune Defic Syndr, 25*(2), 164-172.

Pinkerton, S. D., Holtgrave, D. R., & Valdiserri, R. O. (1997). Cost-effectiveness of HIV-prevention skills training for men who have sex with men. *AIDS, 11*(3), 347-357. doi:Doi 10.1097/00002030-199703110-00013

Plankey, M. W., Ostrow, D. G., Stall, R., Cox, C., Li, X., Peck, J. A., & Jacobson, L. P. (2007). The relationship between methamphetamine and popper use and risk of HIV seroconversion in the multicenter AIDS cohort study. *Journal of acquired immune deficiency syndromes (1999), 45*(1), 85.

Platt, R., Rice, P. A., & Mccormack, W. M. (1983). Risk of Acquiring Gonorrhea and Prevalence of Abnormal Adnexal Findings among Women Recently Exposed to Gonorrhea. *Jama-Journal of the American Medical Association, 250*(23), 3205-3209. doi:DOI 10.1001/jama.250.23.3205

Pope, J. C. (2008). Fear of crime and housing prices: Household reactions to sex offender registries. *Journal of Urban Economics, 64*(3), 601-614.

Poulos, C., Yang, J., Levin, C., Van Minh, H., Giang, K. B., & Nguyen, D. (2011). Mothers' preferences and willingness to pay for HPV vaccines in Vinh Long Province, Vietnam. *Social Science & Medicine, 73*(2), 226-234.

Protière, C., Donaldson, C., Luchini, S., Moatti, J. P., & Shackley, P. (2004). The impact of information on non-health attributes on willingness to pay for multiple health care programmes. *Social Science & Medicine, 58*(7), 1257-1269.

Purcell, D. W., Wolitski, R. J., Hoff, C. C., Parsons, J. T., Woods, W. J., & Halkitis, P. N. (2005). Predictors of the use of viagra, testosterone, and antidepressants among HIV-seropositive gay and bisexual men. *AIDS, 19,* S57-S66.

Puzzanchera, C., Sladky, A., & Kang, W. (2011). Easy Access to Juvenile Populations: 1999-2010. http://www.ojjdp.gov/ojstatbb/ezapop/

Rosen, S. (1974). Hedonic prices and implicit markets: product differentiation in pure competition. *The Journal of Political Economy*, 34-55.

Ross, G. H., & Sternquist, M. C. (2012). Methamphetamine exposure and chronic illness in police officers significant improvement with sauna-based detoxification therapy. *Toxicology and industrial health, 28*(8), 758-768.

Rudstrom, M. (2004). Determining implicit prices for hay quality and bale characteristics. *Applied Economic Perspectives and Policy, 26*(4), 552-562.

Ryan, A. M., & Spash, C. L. (2011). Is WTP an attitudinal measure? Empirical analysis of the psychological explanation for contingent values. *J Econ Psychol, 32*(5), 674-687.

Schiffer, J. T., Mayer, B. T., Fong, Y., Swan, D. A., & Wald, A. (2014). Herpes simplex virus-2 transmission probability estimates based on quantity of viral shedding. *Journal of The Royal Society Interface, 11*(95), 20140160.

Schmiege, S. J., Broaddus, M. R., Levin, M., & Bryan, A. D. (2009). Randomized trial of group interventions to reduce HIV/STD risk and change theoretical mediators

among detained adolescents. *J Consult Clin Psychol, 77*, 38-50. doi:10.1037/a0014513

Schroeder, S. A. (2007). We can do better—improving the health of the American people. *N Engl J Med, 357*(12), 1221-1228.

Shono, A., Kondo, M., Ohmae, H., & Okubo, I. (2014). Willingness to pay for public health services in rural Central Java, Indonesia: Methodological considerations when using the contingent valuation method. *Social Science & Medicine, 110*, 31-40.

Shoptaw, S., & Reback, C. J. (2007). Methamphetamine use and infectious disease-related behaviors in men who have sex with men: implications for interventions. *Addiction, 102*(s1), 130-135.

Shoptaw, S., Reback, C. J., Peck, J. A., Yang, X., Rotheram-Fuller, E., Larkins, S., . . . Hucks-Ortiz, C. (2005). Behavioral treatment approaches for methamphetamine dependence and HIV-related sexual risk behaviors among urban gay and bisexual men. *Drug and alcohol dependence, 78*(2), 125-134.

Shukla, R. K., Crump, J. L., & Chrisco, E. S. (2012). An evolving problem: Methamphetamine production and trafficking in the United States. *International Journal of Drug Policy, 23*(6), 426-435.

Sickmund, M., Sladky, T. J., Kang, W., & Puzzanchera, C. (2011). Easy Access to the Census of Juveniles in Residential Placement. http://www.ojjdp.gov/ojstatbb/ezacjrp/

Siegel, M. (2002). The effectiveness of state-level tobacco control interventions: a review of program implementation and behavioral outcomes. *Annu Rev Public Health, 23*(1), 45-71.

Sloan, F. A. (2004). *The price of smoking*: MIT press.

Slovic, P. (2000). What does it mean to know a cumulative risk? Adolescents' perceptions of short-term and long-term consequences of smoking. *Journal of behavioral decision making, 13*(2), 259.

Slovic, P. (2001). Cigarette smokers: rational actors or rational fools?

Smith, D. K., Herbst, J. H., & Rose, C. E. (2015). Estimating HIV protective effects of method adherence with combinations of preexposure prophylaxis and condom use among African American men who have sex with men. *Sexually Transmitted Diseases, 42*(2), 88-92.

Søgaard, R., Lindholt, J., & Gyrd-Hansen, D. (2012). Insensitivity to Scope in Contingent Valuation Studies. *Applied health economics and health policy, 10*(6), 397-405.

Stall, R., Paul, J., Barrett, D., Crosby, G., & Bein, E. (1999). An outcome evaluation to measure changes in sexual risk-taking among gay men undergoing substance use disorder treatment. *Journal of studies on alcohol, 60*(6), 837-845.

Stall, R., & Purcell, D. (2000). Intertwining epidemics: a review of research on substance use among men who have sex with men and its connection to the AIDS epidemic. *AIDS and Behavior, 4*(2), 181-192.

Stice, E., Shaw, H., & Marti, C. N. (2006). A meta-analytic review of obesity prevention programs for children and adolescents: the skinny on interventions that work. *Psychol Bull, 132*(5), 667.

Sudakin, D., & Power, L. E. (2009). Regional and temporal variation in methamphetamine-related incidents: applications of spatial and temporal scan statistics. *Clinical Toxicology, 47*(3), 243-247.

Summers, T., Kates, J., & Murphy, G. (2002). Tip of the Iceberg: Youth and HIV/AIDS. Menlo Park, CA: The Henry J. Kaiser Family Foundation.

Sutton, S. (2004). Determinants of health-related behaviours: Theoretical and methodological issues. In S. Sutton, A. Baum, & M. Johnston (Eds.), *The Sage handbook of health psychology* (pp. 94-126). London: Sage.

Sweat, M., O'Donnell, C., & O'Donnell, L. (2001). Cost-effectiveness of a brief video-based HIV intervention for African American and Latino sexually transmitted disease clinic clients. *AIDS, 15*(6), 781-787.

Tao, G., & Remafedi, G. (1998). Economic evaluation of an HIV prevention intervention for gay and bisexual male adolescents. *JAIDS Journal of Acquired Immune Deficiency Syndromes, 17*(1), 83-90.

Tita, G. E., Petras, T. L., & Greenbaum, R. T. (2006). Crime and residential choice: a neighborhood level analysis of the impact of crime on housing prices. *Journal of Quantitative Criminology, 22*(4), 299-317.

Troy, A., & Grove, J. M. (2008). Property values, parks, and crime: A hedonic analysis in Baltimore, MD. *Landscape and urban planning, 87*(3), 233-245.

Tung, G.-S., Lai, P.-Y., & Huang, H.-W. (2012). Using the hedonic price model for the international hotels in Taiwan. *Asian Journal of Business and Management Sciences, 1*(1), 189-196.

van den Berg, B., Brouwer, W., Exel, J. v., & Koopmanschap, M. (2005). Economic valuation of informal care: the contingent valuation method applied to informal caregiving. *Health Economics, 14*(2), 169-183.

van Valkengoed, I. G. M., Postma, M. J., Morré, S. A., van den Brule, A. J. C., Meijer, C. J. L. M., Bouter, L. M., & Boeke, A. J. P. (2001). Cost effectiveness analysis of a population based screening programme for asymptomatic Chlamydia trachomatis infections in women by means of home obtained urine specimens. *Sexually Transmitted Infections, 77*(4), 276-282.

Varghese, B., Maher, J. E., Peterman, T. A., Branson, B. M., & Steketee, R. W. (2002). Reducing the risk of sexual HIV transmission: quantifying the per-act risk for HIV on the basis of choice of partner, sex act, and condom use. *Sexually Transmitted Diseases, 29*(1), 38-43.

Vermaire, J. H., Van Exel, N. J. A., Van Loveren, C., & Brouwer, W. B. (2012). Putting your money where your mouth is: Parents' valuation of good oral health of their children. *Social Science & Medicine, 75*(12), 2200-2206.

Wang, L. Y., Davis, M., Robin, L., Collins, J., Coyle, K., & Baumler, E. (2000). Economic Evaluation of Safer Choices: A School-Based Human Immunodeficiency Virus, Other Sexually Transmitted Diseases, and Pregnancy Prevention Program. *Arch Pediatr Adolesc Med, 154*(10), 1017-1024. doi:10.1001/archpedi.154.10.1017

Whitty, J. A. (2012). Insensitivity to Scope in Contingent Valuation Studies. *Applied health economics and health policy, 10*(6), 361-363.

Zimmerman, M., Rappaport, J., & Seidman, E. (2000). Empowerment theory: Psychological, organizational, and community levels of analysis. Handbook of community psychology. 2000. In J. Rappaport & E. Seidman (Eds.), *Handbook of community psychology* (pp. 43-63). New York: Plenum Press.