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Naloxone Access and Opioid Use: A Theoretical Analysis

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Abstract

Naloxone, commonly known by the brand name Narcan, is a medication that reverses the potentially fatal effects of an opioid overdose. Amidst the opioid epidemic that has taken tens of thousands of lives each year, many policies have been enacted to increase the public's access to naloxone, allowing non-medical personnel to save lives. There have been two distinct reactions to these policies. Those that support the policies state that harm reduction measures are necessary to save lives. Those that oppose the policies claim that by providing naloxone, states may be increasing risky opioid use - suggesting that naloxone leads to moral hazard. I examine this idea theoretically. Using an expected utility model, I model an individual's decision to use opioids. I show that individuals choose to take higher quantities of opioids as the probability of receiving naloxone increases. I also investigate the motivation behind an individual's choice to choose a "riskier" but cheaper opioid and find that individuals are willing to make this switch to cheaper and riskier substitutes when the decrease in prices sufficiently offsets the difference in risk, or if naloxone access is sufficiently high. This analysis can be used to inform policy recommendations in the future as many U.S. states focus on increasing the public's access to naloxone. Recommendations will differ depending on if the focus is harm reduction or the mitigation of potential moral hazard.

Contents

1 Introduction

The opioid epidemic devastating the United States has been called the worst drug crisis in American history (Bosman, 2015). From 2000 to 2016, there was a 200% increase in the rate of overdoses involving opioids (Rudd et al., 2016). In 2017, 47,600 people in the U.S. died of an opioid involved overdose, making up 67.8% of the total drug overdose deaths in the U.S. that year (Scholl et al., 2018). By October 2017, the Trump Administration had declared the opioid crisis to be a public health emergency (Davis, 2017).

In response to the epidemic, U.S. states have enacted policies with the goal of reducing opioid abuse and mortality. A recent trend in public policies has been increasing availability of naloxone, a lifesaving medication that counters the effects of an opioid overdose and can be administered by laypersons (any non-medical personnel).[1] Although laws vary by state, as of July 2017 every state had passed some form of legislation to increase the public's access to naloxone (Davis, 2018).

However, although naloxone has saved many lives, it does not come without controversy. Critics of naloxone worry that the medication is enabling those addicted to opioids. They claim it may incentivize people to continue to use opioids, potentially in higher quantities, because they will rely on naloxone to save them (Hilton, 2018). Politicians who oppose naloxone justify their opinions with this line of reasoning. A well known critic of naloxone is former Maine governor Paul LePage who frequently spoke negatively of the medication and tried to limit access through legal pathways (Stone, 2018). LePage has called naloxone "an excuse to stay addicted", and in a veto message he wrote it "perpetuate[s] the cycle of addition" (Mistler, 2014; Russel, 2017).

This paper will theoretically analyze an individual's choice to use opioids given the likelihood they will receive naloxone if they overdose. I investigate how naloxone access may affect an individual's choice of opioid type and quantity. This analysis can inform future policy recommendations.

[1] For more information on naloxone and naloxone policies, see Sections 2.5 and 2.6.

Naloxone has only been administered by laypersons in the past five years, so there are a limited number of papers in the space of naloxone access. Rees et al. (2017) find that naloxone access laws are associated with the reduction of opioid related deaths two or more years after the law is adopted. They find this relationship is stronger for non-heroin related opioid overdoses.

However, in the paper most closely related to this paper, Doleac and Mukherjee (2018) find less promising results about naloxone's welfare implications. Their analysis suggests that increased access to naloxone increases opioid use and did not decrease net opioid mortality. They argue that there may be moral hazard associated with naloxone.

Moral hazard is defined as any changes in behavior that come from being insured (Nyman, 2003). Although Doleac and Mukherjee (2018) are the first to explore moral hazard in the context of naloxone, moral hazard appeared in economics literature in the 20th century, most often appearing in insurance literature (Rowell and Connelly, 2012). Since then, economists have expanded the term's use while investigating how mitigation of risk may lead to increased risky behavior in a variety of contexts. For example, when an HIV treatment reduced both the likelihood of contracting HIV and the cost of infection, optimal behavior shifted and partners were more likely to participate in risky sex (Chan et al., 2016). Cohen and Einav (2003) analyze the potential moral hazard of seat belts laws, finding that they do not increase fatalities by encouraging reckless driving.

This paper will contribute to both moral hazard and naloxone literatures. First, I investigate the potential moral hazard of naloxone using a theoretical model, which to the best of my knowledge has not been done previously. This model depicts an individual's choice of opioid quantity based on naloxone availability. Additionally, I characterize when an individual will switch to a cheaper but riskier type of opioid, which has also not been modeled in economics literature. This paper also uses the setup of a social planner's problem to inform naloxone policy recommendations, which differ depending how harm reduction is weighted verses moral hazard.

This paper is organized as follows. Section 2 provides background on the opioid epidemic, existing policies, facts about naloxone, and naloxone specific policies. Section 3 includes a toy model and numeric examples. Section 4 then introduces the full theoretical model and its implications, and concludes with the setup of a social planner's problem. Section 5 is a discussion of the results from the model and Section 6 is the conclusion. Lastly, Section 7 is an appendix with derivations of equations.

2 Background

2.1 What are Opioids?

Opioids are a class of drug naturally derived from opium, which is extracted from the poppy plant, or made synthetically in a lab. Opioid painkillers, such as oxycodone, morphine, and codeine, are available by prescription to treat severe pain. However, they also provide short term highs, and for this reason are used illicitly for non-medical reasons (DEA, 2017).

Prescription painkillers have been thought of as a "gateway" to drugs such as heroin, a highly addictive non-synthetic opioid (DEA, 2017). Over 80% of heroin users in 2008-2010 reported that they used prescription pain killers for non-medical use before using heroin (Jones, 2013).

More recently, another major abused opioid is fentanyl. Fentanyl is a synthetic opioid and is one-hundred times stronger than morphine and fifty times more potent than heroin. It is often mixed into heroin to make it stronger, or may even be disguised as heroin (DEA, 2017).

2.2 History of the Opioid Epidemic

Almost 450,000 people died from an opioid overdose in 1999-2018 in the United States. The Center for Disease Control describes the epidemic in three distinct waves: prescription opioids, heroin, and synthetic opioids (CDC, 2018).

The opioid crisis began in the U.S. in the 1990s when there was a surge in the prescription of opiate pain killers - from 1997 to 2005 there was over a 500% increase in these prescriptions (Unick et al., 2014). Although many of these prescriptions were for legitimate medical reasons, it also allowed easier access to those with opioid use disorders. Prescription opioid related mortality rapidly increased until 2010 and then began to level off. The same year, there was a surge in heroin related deaths, which rose rapidly for the next five years. This can be partially attributed to an increase in heroin supply, which decreased heroin costs and increased its purity. This led many people to transition from prescription opioids to heroin (Unick et al., 2014). In 2013, a third wave of the opioid epidemic began, as deaths related to synthetic opioids, primarily fentanyl, skyrocketed (CDC, 2018). Unlike heroin, fentanyl can be produced relatively quickly in a lab, instead of requiring the cultivation of poppy plants. Therefore, prices of fentanyl typically remain lower than heroin (Hufford and Burke, 2018).

Recently, however, outcomes have begun to improve. In 2018 opioid death rates decreased overall by 2% since 2017. This includes a 13.5% decrease in the prescription opioid death rate, and a 4% decrease in the heroin death rate. Unfortunately, synthetic opioid deaths did rise by 10% (CDC, 2018).

2.3 Economic Impacts of the Epidemic

The epidemic has been very costly to society. A recent report from the Society of Actuaries estimates that the U.S.'s total economic burden from the opioid crisis during 2015 to 2018 was $631 billion. This accounts for not only rising health care costs, but also criminal justice costs, loss of productivity, mortality costs, and government funded programs such as education and family and child assistance (Davenport et al., 2019).

Much of the literature indicates associations between opioid use and the economy. For example, economic downturns lead to increased intensity of pain reliever use and an increase in opioid substance use disorders (Carpenter et al., 2017). Additionally, macroeconomic shocks and rising county unemployment are associated with rising opioid death rates (Hollingsworth et al., 2017). However, economists disagree if the opioid epidemic is related to the decline of labor force participation (Krueger, 2017; Aliprantis et al., 2019; Beheshti, 2019; Currie et al., 2019; Ruhm, 2019).

2.4 Policies

Given the serious economic and social impacts, policy makers have spent the past decade attempting to combat this epidemic. One major supply-side policy was the implementation of Prescription Drug Monitoring Programs (PDMPs) on the state level. PDMPs track opioid prescriptions to deter individuals from receiving opioid prescriptions from multiple doctors so that the medication could be abused. Must access PDMPs require prescribers to record their opioid prescriptions and check their patient's history in the system before prescribing. Must access PDMPs can lower extreme opioid use, but do not have an effect on opioid poisoning incidents (Buchmueller and Carey, 2018). Must access PDMPs are also associated with the reduction of treatment admissions for cocaine and marijuana, two compliments to opioid consumption (Grecu et al., 2019). Unfortunately, PDMPs in general may increase heroin related crime in opioid dense counties, because individuals switch to drugs such as heroin when prescription painkillers become more difficult to access (Mallatt, 2017).

Another supply side strategy was the "abuse-deterrent" reformulation of OxyContin, a brand of oxycodone and one of the most commonly abused opioids. OxyContin is most dangerous to users when the pill is crushed, since it is then typically inhaled or injected. The reformulation made the pills more difficult to crush and dissolve, but there is no evidence that this reformulation reduced opioid overdose deaths. Instead, consumers substituted to synthetic options like fentanyl (Alpert et al., 2018). This reformulation also increased the heroin death rate (Evans et al., 2019).

Over half of the U.S. states have also adopted Good Samaritan Laws (GSLs), which protects anyone who calls for medical assistance from the criminal liability of possession of a controlled substance. However, there is no evidence that GSLs have any significant affect on recreational use of prescription opioids (Rees et al., 2017).

These are many of the well-known and widespread policies surrounding the opioid epidemic, but this is in no means a comprehensive list. Although all policies mentioned above were well intentioned, many still had unintended consequences of users switching to other types of drugs.

2.5 What is Naloxone?

Naloxone is an opioid antagonist commonly referred to by the brand name Narcan. This medication counteracts the potentially lethal effects to the central nervous and respiratory systems caused by an opioid overdose. Naloxone has no effect on the body if opioids are not present. Therefore, it can be used as a preventative measure if an opioid overdose is suspected, but it also will not help with an overdose of any non-opioid drug (NIDA, 2019).

However, the effects of naloxone only last from thirty to ninety minutes, and an opioid overdose may last longer than this. As a result, an individual may begin overdosing again after the naloxone wears off even if they haven't used opioids since naloxone had been administered (NIDA, 2019). For this reason, Narcan's website specifies that the individual should receive emergency medical care after receiving naloxone, and they should continue to be monitored in case another dose of naloxone is necessary (ADAPT Pharma Inc., 2019).

Additionally, naloxone often makes the patient experience intense symptoms of opioid withdrawal. These symptoms include sweating, nausea, vomiting, headaches, and tremors Although the side effects are not life threatening, they are an unpleasant experience associated with naloxone (NIDA, 2019).

Intramuscular naloxone, administered through a needle, has been used by medical personnel in the U.S. for over fifty years (DeSimone et al., 2018). However, in 2015 the FDA approved intranasal naloxone, a nasal spray that allows those with minimal to no medical training to administer this life saving medication (FDA, 2015). Support of the medication has continued to increase, especially in 2018 after the U.S. Surgeon General issued an advisory for family and friends of those at risk of an opioid overdose to carry naloxone on their person (Adams, 2018). As support and acceptance of naloxone grows, the number of policies to increase the public's access to naloxone has grown.

2.6 Naloxone Policies

One popular measure to put naloxone into the hands of laypersons is to allow pharmacists to dispense the medication without a prescription. This enables citizens to keep naloxone on their person and in the home of those at risk of overdosing. Today, every state in the U.S. allows pharmacists to dispense naloxone without a prescription, although the methods vary (PDAPS, 2017).

An emerging trend in U.S. law enforcement has been on-duty police officers carrying naloxone. Law enforcement officers are typically larger in numbers than EMTs and other first responders. They are also often the first to arrive on scene, especially in rural areas. There are police departments in every U.S. state have made the decision to equip their officers with naloxone (Davis et al., 2015). However, carrying naloxone is a decision made by the individual police departments, so not every department has made this choice.

States also have different civil, criminal, and/or disciplinary immunity laws for those who administer naloxone. These laws vary for prescribers, laypersons, and "dispensers" - who are typically non-profits and syringe access programs (Davis, 2018). The goal of these laws is to incentivize people to prescribe or administer the drug by promising them different types of immunity.

More than ten U.S. states have also passed laws to stock naloxone in schools. States such as New York, Rhode Island, and Maryland require schools to keep the medication on the premises, whereas other states allow school boards to decide if they want to carry naloxone (Alltucker, 2018).

Aside from legislation, there are other strategies used to increase naloxone use. One of these strategies has been a push to educate more people about how to administer naloxone.

In the beginning of 2020, a county in Tennessee made headlines for teaching children as young as six years old how to administer naloxone during after school programs, reportedly training around 600 in the past three years (Levin, 2020).

Another way to educate the public is by publicly funded advertisements. For example, as part of a statewide initiative in Maine, ads for Narcan are becoming more prevalent. The state has public service announcements running on television channels, ads on city busses, as well as online advertisements (Mundry, 2020). The purpose of this initiative is to raise awareness all over the state that naloxone is available and should be used.

One of the simplest ways to increase naloxone access is to give it away for free. Recently, a new product has entered the market for this purpose, called a NaloxBox. These units are installed in public buildings just like an AED or fire extinguisher, and allow bystanders easy access to naloxone. The company's goal is not only to save lives, but to reduce the stigma associated with opioid overdoses (NaloxBox, 2020). Officials in many states have recognized these boxes, and have announced intentions to install them if they haven't already.

3 Toy Model

This section introduces a toy model of an individual's decision of the optimal quantity of opioids to consume. I use an expected utility framework where the decision maker chooses what quantity of opioids to consume given the monetary cost and naloxone availability. I begin with the model setup and then demonstrate how the model works with numeric examples.

3.1 Toy Model Setup

Consider the simple situation where a utility maximizing individual has already made the decision to use an opioid, and is now choosing between two quantities of this opioid, $\hat{q}$ and $\bar{q}$, where $\hat{q} < \bar{q}$. Assume $\hat{q}$ is a low enough quantity that, if chosen, the individual will never overdose and that $\bar{q}$ always leads to an opioid overdose. In this example, I assume that an overdose results in death if naloxone is not administered. Additionally, I assume that this individual will never intentionally seek a fatal overdose.

Let $f(q)$ be the individual's consumption utility as a function of opioid quantity. Define $D < 0$ to be the individual's utility from passing away from an opioid overdose or its complications. Since $\bar{q}$ guarantees an overdose which results in death, $f(\bar{q}) = D$. Let $\hat{q}$ give the individual positive utility, so $f(\hat{q}) > 0 > D$. Additionally, define $c(q)$ be the individual's cost as a function of opioid quantity. Assume $c(q)$ is increasing in q, so $c(\hat{q}) < c(\bar{q})$.

If the individual chooses $\hat{q}$, let their total utility be defined as

$$u(\hat{q}) = f(\hat{q}) - c(\hat{q})$$

If the individual chooses $\bar{q}$, let their total utility be defined as

$$u(\bar{q}) = D - c(\bar{q})$$

Since $\hat{q}$ costs less and has a higher consumption utility than $\bar{q}$, the total utility from $\hat{q}$ will always be greater than $\bar{q}$, $u(\hat{q}) > u(\bar{q})$. Under these conditions, the individual will never choose $\bar{q}$.

Now introduce naloxone to the example. Let n be a binary variable, where $n = 1$ if naloxone is administered and $n = 0$ is naloxone is not administered. If $n = 1$, the individual will survive an overdose, and if $n = 0$ they will not. Assume s is the probability that $n = 1$ and $(1 - s)$ is the probability that $n = 0$, where $s \in [0, 1]$. Since the individual can now survive $\bar{q}$, they can receive positive utility from $\bar{q}$, where $f(\bar{q}) > f(\hat{q})$. The individual's choice is now more complex. They can choose $\hat{q}$ and be guaranteed positive utility, or they may take a gamble with $\bar{q}$ which may yield higher utility than $\hat{q}$ but may result in death instead. The individual's decision is diagrammed in Figure 1.

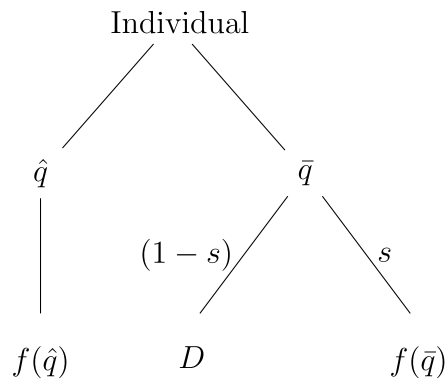

Figure 1.

If the individual chooses $\hat{q}$, their expected utility is the same as before because they have no chance of overdose and therefore do not need naloxone,

$$u(\hat{q}) = f(\hat{q}) - c(\hat{q})$$

However, because there is now a chance of survival if they overdose, if they choose $\bar{q}$ their utility function now depends on if $n = 1$. Therefore, there is a probability s that their utility function is $f(\bar{q}) - c(\bar{q})$, and a $(1-s)$ probability that they overdose and pass away, so their utility is $D - c(\bar{q})$. This expected utility function is below.

$$u(\bar{q}, s) = sf(\bar{q}) + (1-s)D - c(\bar{q})$$

With the introduction of naloxone, under expected utility theory if s is sufficiently high the individual will choose $\bar{q}$. Since $\bar{q}$ is the riskier choice, this suggests the existence of moral hazard, because a higher probability of receiving naloxone may cause the individual to consume a higher quantity of opioids.

3.2 Examples

In this section I demonstrate an individual's choice to switch from the lower quantity of the opioid to the higher, riskier quantity, dependent on naloxone availability. Different risk preference types will have different sensitivities to naloxone access. For the example, I show these differential sensitivities for the three most common risk preferences.

In the following numeric examples I make specific assumptions of the functional forms of these three types of risk preferences. For the risk averse individual, $f(q) = \sqrt{q}$. For the risk neutral individual, $f(q) = q$, and for the risk loving individual, $f(q) = q^2$.

Since I am calculating utility which is ordinal, for the following examples I normalize q to be in the interval $[0, 1]$. Additionally, for the following examples, assume that the cost function is linear, so $c(q) = kq$ where k is the price per unit of q.

I use the values $k = 0.5, D = -0.5, \hat{q} = .1$ and $\bar{q} = 0.9$. The only variable that changes in each example will be s, the probability of receiving naloxone.

3.2.1 Case 1: s = 0

Risk Averse:

$u(\hat{q}) = \sqrt{0.1} - 0.5(0.1) = 0.266$

$u(\bar{q}) = 0 \cdot \sqrt{0.9} - 0.5 - 0.5(0.9) = -0.95$

Since $u(\hat{q}) > u(\bar{q})$, the risk averse individual will choose $q = \hat{q}$.

Risk Neutral:

$u(\hat{q}) = 0.1 - 0.5(0.1) = 0.05$

$u(\bar{q}) = 0 \cdot 0.9 - 0.5 - 0.5(0.9) = -0.95$

Since $u(\hat{q}) > u(\bar{q})$, the risk neutral individual will choose $q = \hat{q}$.

Risk Loving:

$u(\hat{q}) = 0.1^2 - 0.5(0.1) = -.04$

$u(\bar{q}) = 0 \cdot 0.9^2 - 0.5 - 0.5(0.9) = -0.95$

Since $u(\hat{q}) > u(\bar{q})$, the risk loving individual will choose $q = \hat{q}$.

When $s = 0$ there is no chance of receiving naloxone, which guarantees that the individual will pass away if they choose $\bar{q}$. Therefore, I have shown that when $s = 0$, every preference type chooses $\hat{q}$. This is what was discussed at the beginning of Section 3.1. Before naloxone was introduced to the model, the individual always chose $\hat{q}$ and never chose $\bar{q}$.

3.2.2 Case 2: s = 0.7

Risk Averse: $u(\hat{q}) = 0.266$ and $u(\bar{q}) = 0.064$. Since $u(\hat{q}) > u(\bar{q})$, the risk averse individual will choose $q = \hat{q}$.

Risk Neutral: $u(\hat{q}) = 0.05$ and $u(\bar{q}) = 0.03$. Since $u(\hat{q}) > u(\bar{q})$, the risk neutral individual will choose $q = \hat{q}$.

Risk Loving: $u(\hat{q}) = -.04$ and $u(\bar{q}) = -0.033$. Since $u(\hat{q}) < u(\bar{q})$, the risk loving individual will choose $q = \bar{q}$.

Now that the probability of receiving naloxone is sufficiently high (70%), the risk loving individual switches to choosing $\bar{q}$ but the risk neutral and averse individuals continue to choose $\hat{q}$. It is intuitive that the risk averse individual will be the first to switch to $\bar{q}$ than the other risk preferences.

3.2.3 Case 3: s = 0.8

Risk Averse: $u(\hat{q}) = 0.266$ and $u(\bar{q}) = 0.209$. Since $u(\hat{q}) > u(\bar{q})$, the risk averse individual will choose $q = \hat{q}$.

Risk Neutral: $u(\hat{q}) = 0.05$ and $u(\bar{q}) = 0.17$. Since $u(\hat{q}) < u(\bar{q})$, the risk neutral individual will choose $q = \bar{q}$.

Risk Loving: $u(\hat{q}) = -.04$ and $u(\bar{q}) = 0.098$. Since $u(\hat{q}) < u(\bar{q})$, the risk loving individual will choose $q = \bar{q}$.

Now the probability of receiving naloxone is 80% and both the risk neutral and risk loving individual will choose $\bar{q}$. The probability is still not high enough for the risk averse individual to choose $\bar{q}$.

3.2.4 Case 4: s = 0.9

Risk Averse: $u(\hat{q}) = 0.266$ and $u(\bar{q}) = 0.354$. Since $u(\hat{q}) < u(\bar{q})$, the risk averse individual will choose $q = \bar{q}$.

Risk Neutral: $u(\hat{q}) = 0.05$ and $u(\bar{q}) = 0.31$. Since $u(\hat{q}) < u(\bar{q})$, the risk neutral individual will choose $q = \bar{q}$.

Risk Loving: $u(\hat{q}) = -.04$ and $u(\bar{q}) = 0.229$. Since $u(\hat{q}) < u(\bar{q})$, the risk loving individual will choose $q = \bar{q}$.

Now the probability of receiving naloxone is high enough that all preferences would choose $\bar{q}$. This remains true for all $s \geq 0.9$.

Naloxone access changes the consequences of overdosing, so individuals are more willing to take on risky behaviors as s increases. As long as the probability of receiving naloxone is sufficiently high, even a risk averse individual will switch to the riskier quantity $\bar{q}$.

The previous numeric examples are represented visually in Figure 2. With $s \in [0, 1]$ on the x-axis, the graph shows when each preference type switches to the higher quantity, $\bar{q}$. Risk loving individuals switch first, then risk neutral, and lastly risk averse individuals. When $s = 0$ all preferences start at the lower quantity, $\hat{q}$, but by $s = 0.84$ all preferences have switched to the higher quantity. After each preference type switches to the higher quantity it will not switch back for any increase in s.

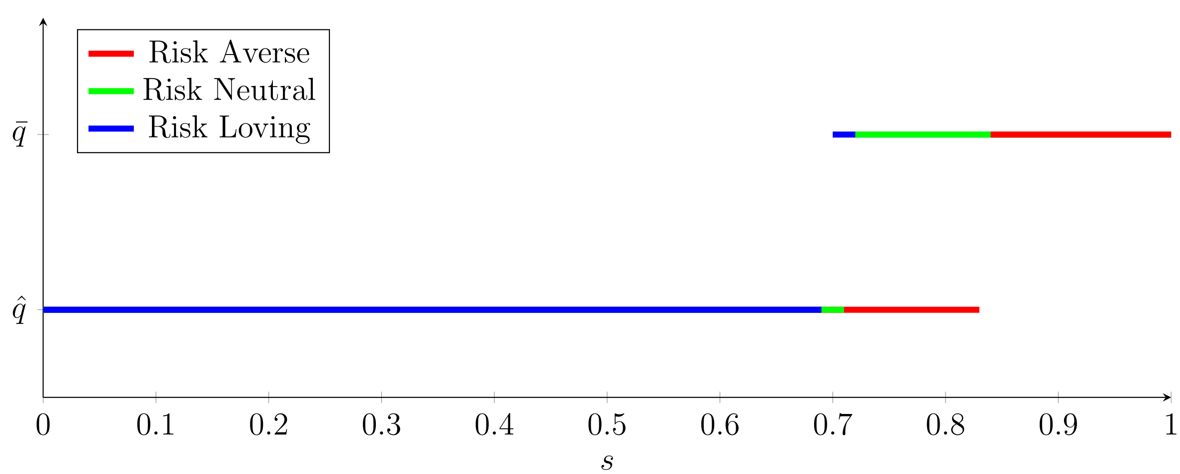

Figure 2.

4 Model

This section continues to use the expected utility framework and intuition from Section 3, but relaxes many of the assumptions.

Section 4.1 sets up this model. Then, Section 4.2 solves for when an individual switches from one opioid to a riskier yet cheaper opioid, given the naloxone availability. Lastly, Section 4.3 outlines a social planner's problem to characterize how a policy maker should approach naloxone access.

4.1 Model Setup

In the toy model I captured how the individual's choice varies under the availability of naloxone. However, this relies on the assumptions that opioid quantity is binary and that only one opioid quantity could cause an overdose. The examples in Section 3.2 assumed specific forms of utility functions and a linear cost function. I now generalize the model to allow for generic utility and cost functions and continuous quantities of opioids while building on the intuition from the example.

Assume that the utility maximizing individual is still choosing a quantity of one type of opioid, but now let the quantity be continuous, $q \in [0, \bar{q}]$. Let $p(q)$ be the probability of overdosing if the individual chooses quantity q. I assume that the probability of overdose is increasing in quantity, $p'(q) > 0$. Additionally, I assume that the highest quantity is the one that guarantees an overdose, $p(\bar{q}) = 1$ and that if an individual takes no opioids the probability of overdosing is zero, $p(0) = 0$.

As in the toy model, let $f(q)$ be the individual's utility as a function of opioid quantity, where $f'(q) > 0$ and $f(0) = 0$. Let $c(q)$, the individual's cost function, be an increasing function of quantity, $c'(q) > 0$.[2]

[2] This cost function only includes the cost of opioids. I am treating the cost of naloxone as negligible because although naloxone has a cost, it is often not a cost paid for by the individual. It may be administered by police officers or other emergency responders, or may be purchased by a friend or family member who carried the dose.

I continue to assume that the individual will never intentionally seek a fatal overdose. Let the utility from passing away be negative, $D < 0$, to ensure it is less than the utility from consuming zero opioids.

As in the toy model, let n be a binary variable, where $n = 1$ if naloxone is administered and $n = 0$ is naloxone is not administered. Assume s is the probability that $n = 1$ and $(1-s)$ is the probability that $n = 0$, where $s \in [0, 1]$. Assume that if naloxone is administered the individual is guaranteed to survive an overdose.[3]

It is important to note that each function in the model is unique to that individual. Therefore, $p(q)$ takes into consideration factors that may make one individual more likely to overdose than another, such as drug tolerance. The cost function, $c(q)$, also accounts for the fact that individuals may be able to procure opioids at different prices based on factors such as location. Additionally, individuals all have different levels of access to naloxone, depending on their state's laws, the response times of their local first responders, if bystanders carry naloxone, etc. This is taken into consideration by the parameter s.

The individual's expected utility from opioid use is below.

$$EU = p(q)[sf(q) + (1 - s)D - c(q)] + (1 - p(q))[f(q) - c(q)]$$

The probability of receiving naloxone, s, is a parameter, so when examining the individual's expected utility, it is for a fixed value of s. I am interested in how the individual's expected utility changes as this parameter changes, which I examine in my first result.

Result 1 *The decision maker's utility is increasing in naloxone access.*

[3]For simplicity, I assume that if naloxone is administered the individual will survive the overdose. In reality, depending on how much of an opioid is in their system, an individual may continue overdosing after the naloxone has worn off, and may need to be given a second or even third dose of naloxone.

By The Envelope Theorem:

$$\begin{aligned}\frac{dv(s)}{ds} &= \frac{\partial u(q,s)}{\partial s} + \frac{\partial u(q,\bar{s})}{\partial q} \times \frac{dq}{ds} \\ &= \frac{\partial u(q,s)}{\partial s} \\ &= p(q)\big[f(q) - D\big]\end{aligned}$$

The derivative of utility with respect to q when s is fixed is equal to zero, therefore the right addend goes to zero. As a result, the total derivative of the utility function with respect to the parameter s is equivalent to the partial derivative of the utility function with respect to s.

Intuitively, the result depends on $p(q)$, since the availability of naloxone only matters if the individual overdoses. Then, $p(q)$ is multiplied by the difference between the utility from consumption and the utility from passing away. Since D is always negative, this difference is always positive. Therefore, since a probability is being multiplied by a positive number, $\frac{dv(s)}{ds}$ is always positive. This tells us that expected utility will always increase in s. Since naloxone will save the individual's life, it makes it less likely that D is realized. Therefore, it is intuitive that as the probability of receiving naloxone grows the individual will experience higher utility.

In the special case that $p(q) = 1$, the result is the difference between $f(\bar{q})$ and utility from death. On the other extreme, if $p(q) = 0$, the derivative is 0. This is intuitive, because the individual will not overdose so the level of s does not matter.

However, the previous analysis does not address how the individual's optimal choice of q is affected by s. I examine this in my second result.

Result 2 *The decision maker's optimal quantity is increasing in naloxone availability.*

I characterize $\frac{\partial q}{\partial s}$. Partial implicit differentiation yields,

$$\frac{\partial q}{\partial s} = \frac{p(q)\big[D - f(q)\big]}{(1-s)\big[p'(q)D - f'(q)p(q) - f(q)p'(q)\big] + f'(q) - c'(q)} \tag{1}$$

Since $p(q) > 0$, $D < 0$ and $f(q) > 0$, the numerator is always negative. Since $(1-s) \geq 0$ and $p'(q)D - f'(q)p(q) - f(q)p'(q) < 0$, the first term in the denominator is always negative or zero. Thus, the sign of $\frac{\partial q}{\partial s}$ depends on the functional forms of $f(q)$ and $c(q)$.

Consider the extreme case that there is no risk associated with opioid use, that is, $s = 1$. The partial derivative is below.

$$\frac{\partial q}{\partial s} = \frac{p(q)\big[D - f(q)\big]}{f'(q) - c'(q)}$$

Here, the numerator will remain negative but the sign of the denominator depends on the sign of $f'(q) - c'(q)$. Therefore, when there is no risk associated with the opioid the only factor influencing whether the individual will choose another unit of q is the difference between marginal utility and marginal cost of q.

However, when risk is introduced, there is a new possible outcome of death. When this happens, Equation (1) shows that other factors besides the marginal benefit are taken into account in the individual's decision.

Therefore, a sufficient condition for $\frac{\partial q}{\partial s} > 0$ is $f'(q) < c'(q)$. As s increases it is more likely that naloxone will be administered, so the opioid effectively seems less risky to the individual. It is intuitive that an increase in s would increase optimal quantity.

The model currently allows the opioid to have one cost function, $c(q)$. In reality, many factors may contribute to changes in price the individual has to pay for certain types of opioids. Therefore, I characterize how the individual's optimal choice of q changes when the cost function changes. Imagine the cost function increases from $c(q)$ to $\tilde{c}(q)$. Define q^* as the optimal quantity for $c(q)$ and $\tilde{q}^*$ as the optimal quantity for $\tilde{c}(q)$. Since $c(q) \leq \tilde{c}(q)$ then $q^* \leq \tilde{q}^*$. Therefore, the optimal quantity decreases as the cost increases, $\frac{\partial q}{\partial c} < 0$.

4.2 Risk and Cost Tradeoff

In the model thus far I have examined an individuals preferences for one type of opioid. However, in reality it is common for individuals also have the choice of multiple types of opioids, which may have different costs or associated risks. For example, individuals who first use prescription opioids often switch to riskier opioids such as heroin (Mars et al., 2014; Jones, 2013). This section investigates the motivation behind this switching behavior, and attempts to characterize what degree of risk an individual is willing to take based on both how much cheaper the alternative opioid is and naloxone availability.

First, I allow the model to include multiple opioids. Let X be a set of all possible opioids and combinations of these opioids. For example, three elements in X are OxyContin, heroin, and heroin combined with fentanyl. Each $i \in X$ has its own probability, utility, and cost functions. In addition, each $i \in X$ also has a unique quantity that guarantees an overdose, $\bar{q}_i$. Additionally, assume that $D < 0$ is the same for all opioids i, since passing away should have the same utility regardless of drug choice. Thus, the expected utility function with appropriate indexing is below.

$$EU = p_i(q)\big[sf_i(q) + (1-s)D - c_i(q)\big] + (1 - p_i(q))\big[f_i(q) - c_i(q)\big]$$

Next, I must allow for the fact that certain opioids (or combinations of opioids) may be "riskier", or make an individual more likely to overdose, than other opioids. For example, fentanyl is one-hundred times more potent than morphine and fifty times more potent than heroin (DEA, 2017).

To account for this increased risk in the model, I define opioid i as riskier than opioid j if $p_i(q) \geq p_j(q)$ for all q, and $p_i(q) > p_j(q)$ for at least one q. In words, for each quantity the probability of overdosing is equal or greater with opioid i than j, but there must be at least one quantity where opioid j has a higher probability.

Consider opioid i and opioid j, where i is riskier but cheaper than j ($c_j(q) \geq c_i(q)$ for all

q). I am interested how an individual is willing to tradeoff risk and cost.

Result 3.1 *The decision maker will switch to a riskier but cheaper opioid if the decrease in cost offsets the increase in risk.*

Result 3.2 *The likelihood of switching to a cheaper but riskier opioid is increasing in the probability of receiving naloxone.*

I find the point where the individual would switch to the riskier opioid. This is where expected utility of i is greater than expected utility of opioid j. To do this, I set the expected utility of opioid i weakly greater than the expected utility of opioid j and solve for the risk-cost ratio, $\frac{p_i(q)-p_j(q)}{c_i(q)-c_j(q)}$.

Since I am interested in examining the risk-cost tradeoff, I make a simplifying assumption that $f_i(q) = f_j(q)$. With this assumption, opioids only differ in price and risk and their consumption utility is fixed to be the same. This eliminates a source of variation which allows us to solve for a closed solution. Under the assumption that $f_i(q) = f_j(q)$, the result is shown in Equation (2).

$$\frac{p_i(q) - p_j(q)}{c_i(q) - c_j(q)} \geq \frac{1}{(1-s)\big[D - f(q)\big]} \tag{2}$$

Since both sides of the inequality are weakly negative, I will compare the magnitudes for interpretation purposes. The left hand side of the result is the risk-cost ratio. The numerator is the difference in risk of the two opioids, and the denominator is the difference in costs.

The righthand side of the inequality depicts the two outcomes of not receiving naloxone: either the individual overdoses and passes away, or they do not overdose and therefore do not need the naloxone in the first place. The difference between these two utilities is in the denominator, multiplied by the probability that they do not receive naloxone, $1 - s$. When the individual is comparing opioids, not only do risk and price matter, but so do the possible outcomes of not receiving naloxone.

The above inequality is not defined when $s = 1$. However, when $s = 1$ there is no risk associated with either opioid, because the individual is guaranteed to be saved if they do overdose. Therefore, the individual would choose the cheapest opioid available to them.

The inequality above tells us that there are two cases when the individual would switch to the riskier opioid. First, the individual would be willing to switch if the denominator of the right side is sufficiently small. This happens when s increases. Intuitively, a higher s reduces the perceived risk of taking opioids, reducing the magnitude of the aftermath of an overdose by making them more likely to be revived.

The second case is when the cost of i is sufficiently less than the cost of j, which offsets the difference between the risks of the opioids.

Therefore, the willingness of an individual to substitute to a riskier opioid increases when they are more likely to be revived with naloxone, or if the difference between the costs of the opioids is sufficiently large.

4.3 Social Planner's Problem

As found in the previous model, there is incentive for individuals to consume higher opioid quantities or switch to riskier opioids as naloxone access increase. This leads to a tension between harm reduction and moral hazard. To think about a how a policy maker approaches these competing interests, I set up a social planner's problem.

Assume that the social planner is considering policies that would directly affect a specific population, whether this be a town, state, etc. For the purposes of the following definitions, assume the utility function is the utility for a specified year.

Remember that the model above solves for an individual's optimal quantity of opioid for one use. Agents in this population will choose different quantities of opioids, and will use opioids a different number of times during the year. As an aggregate measure, let Q_n be the total quantity of non-medical opioids consumed in one year in this population for a given naloxone availability. Then, let Q_o be the total quantity of opioids that would have been consumed in this population if naloxone did not exist.

Since Q_n and Q_o are sums of the optimal quantities discussed in the model, they are determined by the distribution of risk parameters in the population, the probability of receiving naloxone, the cost of opioids, and the number of people in the population. I use this aggregated notation so that additional assumptions are not needed for all of these parameters.

Additionally, the model shows that when naloxone is present quantity is higher, which will remain true for sums. Thus, $Q_n \geq Q_o$.

Let L be the total number of lives that would be saved from naloxone in this year. I will use the quality-adjusted-life-year (QALY) as a measure of how the planner values a human life. The QALY indexes the length of a life and the quality of a life into one number (Prieto and Sacristán, 2003). To allow for heterogeneity in QALYs, for all L individuals whose lives are saved, they each have a QALY_l.

In the model, an individual chooses their optimal opioid quantity based off of s, the probability of receiving naloxone. I assume that there is some naloxone available on the private market and let N be the number of additional naloxone doses a planner would have to provide in this year to make the probability of acquiring naloxone equal to s. Therefore, N is the contribution to total naloxone doses from public policies.

Since N determines s, and s determines an individual's optimal quantity and if they overdose, both Q_n and L are implicitly functions of N.

Define p as the price the planner has to pay for each dose of naloxone, so Np is the total cost of naloxone the planner would have to fund that year. Lastly, define $\lambda > 0$ as a weighting parameter that captures how much the social planner is weights lives saved.

The social planner's utility function is below.

$$U = -\Big(Q_o - Q_n\Big)^2 + \lambda \sum_{l=1}^{L} \text{QALY}_l - Np$$

The first term is a quadratic loss function which accounts for the extra quantity of opioids used when the quantity of naloxone is N. This term represents the moral hazard from naloxone. As naloxone becomes more available, N increases, so Q_n increases. Q_o remains the same, therefore $\left(Q_o - Q_n\right)^2$, or moral hazard, also increases. Thus, since a rising N increases the magnitude of moral hazard, it subsequently decreases the social planner's utility.

The second term represents the total value of all lives saved from naloxone, and is weighted by λ. This essentially puts a value on naloxone's harm reduction. The social planner's utility is increasing in the number of lives saved.

The last term is the monetary cost to society for purchasing naloxone. Although I assume naloxone's cost is negligible for an individual, it does cost a substantial amount of money to buy naloxone in large quantities to provide to the public. Thus, the planner needs to take this into account, and it is utility decreasing.

Next, I examine the optimal policy using a social planner's problem. While I could solve for the optimal quantity of N, N is dependent the exact functional forms of both the social planner and decision maker's utility functions, as well as the distribution of risk parameters in the population. Therefore, a closed solution will not offer much insight. Instead, I will qualitatively characterize the implications for policies.

Ultimately, a policy maker faces a choice of how they value moral hazard verses harm reduction. Their policies will crucially depend on the value of λ. As λ increases the planner is putting a higher weight on harm reduction. Thus, the policies should focus on increasing N, which would therefore increase the probability of the individual receiving naloxone. As λ decreases, the social planner is putting a higher value on moral hazard. Their optimal policy would be to reduce N to minimize moral hazard.

N is increasing in λ, but there are other factors that affect the optimal N. Higher monetary costs per unit of N will decrease the optimal quantity. Additionally, N is highly dependent on the risk preferences of individuals in the population. Recall from the examples in Section 3.2 that different risk preferences have different sensitivities to naloxone, which influence their choice of opioid quantity. Since Q_n is an aggregate measure of opioid quantity consumed, its magnitude depends on the distribution of risk parameters in the population. Therefore, the severity of moral hazard, or the magnitude of $\left(Q_o - Q_n\right)^2$ also depends on the population's risk preferences. Populations with a large amount of risk loving individuals should have a lower N than one with many risk averse individuals.

5 Discussion

The model yields many important results. First, I find that regardless of risk preference individuals will choose to consume a quantity of opioid that they know to be risky if the probability of being revived is sufficiently high. This is evidence of the moral hazard effects of naloxone that has sparked the controversy surrounding the medication. It is important to note, however, that the amount of moral hazard created depends on risk preferences. In Section 3.2 I show that different risk preferences correspond to different sensitivities to naloxone policies, specifically that risk loving individuals are the most sensitive.

Next, via The Envelope Theorem, I find that an individual's utility increases as the probability of receiving naloxone increases. This indicates that increased naloxone availability is welfare improving for individuals. However, this does not necessarily mean that naloxone is welfare improving for a population.

Although naloxone is welfare increasing for individuals, I also find that the individual's choice of opioid quantity increases with naloxone access. This is further evidence of moral hazard, as consuming higher quantities is a risky behavior, it makes the individual more likely to overdose.

I also find the conditions where an individual will switch to a cheaper yet riskier opioid. There are two results. First, the individual will switch to the cheaper yet riskier opioid when the difference in costs is large enough. This is common in real life when users originally become addicted to prescription painkillers but switch to cheaper drugs such as heroin or synthetic opioids.

The second switching condition is that if the probability of receiving naloxone is sufficiently high, then the individual is more likely to switch to the riskier drug. This is intuitive because naloxone lowers the associated risk, so the “risky” drug now appears to be less so. It is another mechanism of how moral hazard is generated from naloxone.

Lastly, my setup of the social planner’s problem indicates how a policy maker has to choose how they weight moral hazard and harm reduction to determine the optimal policies. They may choose their weighting based on their own beliefs, political pressures, or other external factors.

6 Conclusion

My analyses focus on what happens when the probability of receiving naloxone increases. They suggest that increasing naloxone availability is beneficial to those with opioid use disorders because it increases their utility and reduces the mortality risk associated with opioid use.

From a policy perspective, however, my analyses do provide evidence of the tradeoff between harm reduction and moral hazard. On one hand, naloxone decreases the number of deaths related to opioid overdoses. On the other hand, naloxone reduces the risk associated with taking opioids, thus there is some risk of encouraging riskier opioid use. Therefore, when designing their optimal policy, policy makers need to acknowledge how they weight harm reduction verses moral hazard.

If a policy maker wants to focus on saving as many lives as possible from the opioid epidemic, they are weighting harm reduction higher than moral hazard and should focus on increasing the availability of naloxone. Many of the existing strategies and policies to do so are described in Section 2.6. Much progress has been made in this area, such as all U.S. state allow pharmacists to dispense naloxone without a prescription, but more can be done.

For example, states can incentivize police departments to carry naloxone by providing the medication free of charge to the departments. An example of this is the Maine Attorney General's Office, which provides naloxone to any department that asks (Mills, 2018). Increasing police department participation targets populations living in rural areas, as police officers are often first to the scene of an overdose (Burns, 2016).

On a local level, policy makers can work to make free naloxone widely available. For example, they can provide naloxone in public buildings, such as in NaloxBoxes, or equip school nurses with naloxone. They can also use resources to raise public awareness of the medication through TV commercials and advertisements.

Policy makers worried about moral hazard, however, will not want to increase naloxone and will likely be hesitant about these policies. Although they may want to focus on other supply and demand side policies that address the opioid crisis, they should not dismiss naloxone completely.

First, the model demonstrates that individuals with different risk preferences have different sensitivities to naloxone policies. The model focuses on an individual's choice, but to focus on policy one should focus on societal responses and aggregate these measures. Thus, the distribution of risk parameters in the relevant population affects the quantity of moral hazard. Since risk loving individuals are more sensitive to increased naloxone access, a population made largely of risk loving individuals likely will demonstrate a lot of moral hazard. In this case the policy maker should be hesitant about widespread naloxone access. However, if a large proportion of the population is risk neutral or risk loving, moral hazard should be less of a concern.

Since moral hazard may depend on the population, policy makers can supplement naloxone availability with demand side measures, such as increasing treatment programs. While naloxone may save an individual from an overdose, it is not a cure for an opioid use disorder. Therefore, naloxone can be used in tandem with treatment programs and other infrastructure which focus on long term solutions for the opioid epidemic.

Another reason not to completely dismiss naloxone is because similar policies have proven effective. Before naloxone, there were other controversial harm reduction policies put forward to promote health among drug users. An example is needle exchange programs, which disincentivize intravenous drug users sharing needles, slowing the transmission of infections such as HIV. In 2014, Scott County, Indiana showed signs of an HIV outbreak among intravenous drug users. Experts informed the state they should allow clean syringe programs to mitigate future infections. The governor, however, was opposed to this harm reduction method because he felt it condoned drug use. As a result, he did not allow needle exchange programs until the outbreak was already large in numbers (Gonsalves and Crawford, 2020). Gonsalves and Crawford (2018) estimate that 127 HIV cases could have been averted if this harm reduction method had been implemented in a timely manner. Needle exchanges are similar to naloxone in that both create a fear of enabling drug use, but both are also effective public health solutions.

Even if a policy maker is hesitant about naloxone's potential moral hazard, naloxone can certainly work together with other policies to curb the opioid problem, and does not need to be the only policy focus.

Shifting away from naloxone access, there are other policies to limit opioid deaths that policy makers can focus on. They can, for example, target the supply of opioids. My model suggests that if a risky opioid is cheap enough, an individual will likely switch to this riskier drug, which in turn leads to more deaths. Therefore, if policy makers allocate more resources to the disruption of the supply of heroin and fentanyl, prices will increase and individuals will be less likely to switch to these more fatal drugs.

For future research, it would be important to quantify the moral hazard effects of naloxone. As discussed previously, risk preferences will determine the optimal magnitude of naloxone in a population. To quantify moral hazard effects, one would need to find the distribution of risk preferences in a population.

Other forms of future research involve relaxing the many assumptions that this model still relies on. For example, I assume that naloxone is guaranteed to save an individual's life when overdosing. However, naloxone may wear off before the overdose does and many individuals need naloxone to be administered more than once - therefore, it is possible to still pass away after receiving naloxone once. The model could be improved to account for the potential requirement of multiple naloxone doses.

Additionally, my model is interested in the health impacts of opioid use, and the risk associated with health. The model could be enriched by thinking about a different kind of risk associated with opioid use, specifically the legal impacts of partaking in illicit activities. This may not influence the quantity of the opioid the individual chooses, but it likely has some effect in the switching behavior to other types of opioids.

Lastly, the model currently assumes that naloxone itself does not decrease utility. However, patients often experience opioid withdrawal symptoms after receiving the medication, which make them incredibly uncomfortable (NIDA, 2019). To enrich the model, this potential decrease in negativity from naloxone could be quantified and taken into consideration by the individual.

7 Appendix

1. Derivation of Result 2.

$$
\begin{aligned}
EU &= p(q)\big[sf(q) + (1-s)D - c(q)\big] + (1-p(q))\big[f(q) - c(q)\big] \\
EU &= sf(q)p(q) + p(q)D - sp(q)D + f(q) - c(q) - p(q)f(q) \\
\frac{\partial}{\partial s}\Big[EU\Big] &= \frac{\partial}{\partial s}\Big[sf(q)p(q) + p(q)D - sp(q)D + f(q) - c(q) - p(q)f(q)\Big] \\
0 &= f(q)p(q) - p(q)D + \frac{\partial q}{\partial s}\Big[(s-1)(f'(q)p(q) + f(q)p'(q)) + (1-s)p'(q)D + f'(1) - c'(q)\Big] \\
p(q)(D - f(q)) &= \frac{\partial q}{\partial s}\Big[(1-s)\big[p'(q)D - (f'(q)p(q) + f(q)p'(q))\big] + f'(1) - c'(q)\Big] \\
\frac{\partial q}{\partial s} &= \frac{p(q)\big[D - f(q)\big]}{(1-s)\big[p'(q)D - f'(q)p(q) - f(q)p'(q)\big] + f'(q) - c'(q)}
\end{aligned}
$$

2. Derivation of Results 3.1 & 3.2.

$$
\begin{aligned}
&p_i(q)\big[sf(q) + (1-s)D - c_i(q)\big] + (1-p_i(q))\big[f(q) - c_i(q)\big] \\
&\geq p_j(q)\big[sf(q) + (1-s)D - c_j(q)\big] + (1-p_j(q))\big[f(q) - c_j(q)\big]
\end{aligned}
$$

$$
\begin{aligned}
&p_i(q)[(1-s)[D - f_i(q)]] \geq p_j(q)[(1-s)[D - f_j(q)]] + c_i(q) - c_j(q) \\
&\frac{p_i(q) - p_j(q)}{c_i(q) - c_j(q)}\big[(1-s)D - f(q)\big] \geq 1 \\
&\frac{p_i(q) - p_j(q)}{c_i(q) - c_j(q)} \geq \frac{1}{(1-s)D - f(q)}
\end{aligned}
$$

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