The Opioid Crisis and Secondary Markets: Evidence from a Laboratory Experiment*

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Abstract

The opioid crisis is responsible for hundreds of thousands of deaths and trillions of dollars in costs. The secondary market for opioids contributes substantially to those numbers. Nevertheless, the welfare consequences of closing secondary market distribution remain ambiguous. Although shutting down the secondary market could help alleviate the health threat induced by the drug diversions, it could also trigger increased unnecessary prescriptions. Drawing on Schnell's (2017) model of secondary markets and the opioid crisis, we design a laboratory experiment to investigate how secondary markets affect patient and physician behaviors. We find that when a secondary market is present, patients visit physicians more frequently and physicians provide more prescriptions than when there is no secondary market available. Consequently, we find that shutting down this distribution channel reduces total consumption of opioids, and positively impacts overall health outcomes. Our results provide clear evidence that policies aimed at restricting secondary markets can contribute significantly to mitigating the opioid crisis.

Keywords: prescription opioids, secondary market, over prescription

JEL: C91, I11, I12, I18, L10.

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1 Introduction

The ongoing national crisis of opioid deaths has become a severe public health threat necessitating intense attention and action. According to the CDC (2018), in 2017, national drug overdose deaths exceeded the number attributed to gun and car accidents combined. Seventy percent of drug overdose deaths in 2018 were opioid related (46,802 deaths in total). To curtail the opioid crisis, a set of policies have aimed to reduce the legal supply of prescriptions from physicians to patients[1]. However, such policies alone are unlikely to be effective (Bohnert et al. 2011; Dart et al. 2015; Paulozzi et al. 2014; Paulozzi and Ryan 2006), as the vast majority (two-thirds) of misused prescription opioids are accessed through diverted channels on the secondary market (Lipari and Hughes 2017; NASEM 2017).

The literature documents the fact that the legal supply of opioids and secondary market activities are interconnected. Indeed, there is a causal relationship between oversupply of prescription opioids and drug diversions (Powell et al. 2020). However, whether there exists a reverse causality—that is, whether the secondary market also influences physicians' prescription decisions—remains unclear. And while the literature recognizes the detrimental effect of over-prescription (Bohnert et al. 2011; Edlund et al. 2014; Maclean et al. 2020; Schnell and Currie 2018), less research has focused on understanding why physicians persistently over-prescribe even being aware the possible consequences (Lembke 2012).

In this paper, we focus on how the secondary market has contributed to the opioid crisis. We use an experimental environment to help us understand what happens when the secondary market is absent, as compared to when it is present. The comparison also helps shed light on the mechanisms driving over-prescription when the secondary market is present. There are three main motivations for our focus on the secondary market and the opioid crisis. First, the role of the secondary market on physicians' prescription practices is generally unknown. While a previous study by Schnell (2017) estimated the effect the secondary market has had on constraining physicians' prescription practices (as compared to the case without the secondary market), data limitations in that benchmark case have impeded research on this topic. As a result, further experimental work is essential for understanding what happens when there is no secondary market for opioids.

Second, given that prescription opioids have legitimate medical functions, policies aimed at shutting down the secondary market should be understood comprehensively, and in light of the tradeoffs between improving medical access and potentially increasing nonmedical abuse. Unlike most drugs associated with overdose harm to health, prescription opioids are

[1] Policies like introducing abuse-deterrent opioids can lead to substitute use of other dangerous drugs (Alpert et al. 2018). Similarly, crackdown on legal suppliers of pharmaceuticals results in higher rates of opioid abuse and more heroin-related deaths (Meinhofer 2018).

medically necessary if being used to treat chronic and acute pain. Nevertheless, opioids are highly addictive and can also be diverted for non-medical purposes. Under-prescription, just like over-prescription, is an inefficient health outcome for the population and could result in heroin deaths (Alpert et al. 2018; Evans et al. 2019; Kilby 2016). Therefore, before drawing any conclusions about how curtailing over-prescription would impact the opioid crisis, it is important to understand how such policies could impact all the relevant players.

Third, the reason behind the over-prescription by physicians is generally unknown. While over-prescription is linked with overdose death (a fact of which physicians are presumably aware), policies aimed at regulating the prescription practices of physicians are still needed to push the total volume of prescriptions down to the socially optimal level. This paper aims to shed light on the mechanisms driving over-prescription, so as to provide policy implications to address over-prescription and help curtail the opioid crisis.

Using a controlled experiment built on Schnell (2017), this paper tested a series of predictions made by Schnell regarding the effect of the secondary market. Specifically, the theory predicts that shutting down the secondary market would facilitate prescription of opioids; discourage demand from the patients and improve population health outcomes.

Our model implies a tighter prescription standard when the secondary market is present. Intuitively, the reason is that a physician concerns about her revenue and the prescription bestowed population health impact, such that her concern over the prescribed opioids' detrimental effect would impede her from prescribing incautiously, especially when the secondary market enables drug diversions. The theory relies on assumptions about patients' full information about a physician's prescription standards, as well as physicians' knowledge about each patient's intentions for the visit, under equilibrium. In practice, however, limited information and uncertainty over the prescription's population health impact that the physician concerns about may influence him/her to prescribe as the theory predicts.

Our main findings regarding physicians' prescription behavior are in contrast with the theory. Our findings show lower prescription standard (associated with more prescriptions) when the secondary market is present. This tendency toward over-prescription when the secondary market is present aligns with the findings from the natural environment (Buchmueller and Carey 2018), where it can be difficult for physicians to know the true reason for patients' visits. Consistent with the theory, the experiment further reveals that closing the secondary market reduces the demand of those who truly need pain relief and improves the opioid-related public health outcome. Moreover, the extent of the improvement in health is even greater than the theory predicted.

We believe risk attitudes could drive the discrepancy between the theory and our findings regarding physicians' over-prescription behavior[2]. Specifically, the presence of a secondary markets creates uncertainty over the public health consequences that matter to physicians, and that their prescription decisions largely determine. Consequently, physicians' prescription behaviors can be influenced by their own risk attitudes. If there is no extra uncertainty when the secondary markets exist, we should expect to observe similar risk attitudes for physician subjects choosing the same thresholds across treatments.

Our evidence shows that, as compared to when there is no secondary market, a physician who over-prescribes in the presence of a secondary market is more likely to be less risk averse. Such finding reflects the higher uncertainty when secondary markets exist and demonstrates an additional layer of complexity in determining the theoretical effect of secondary markets.

Our results suggest that policies aimed at restricting activities on the secondary market could constitute an important step toward alleviating the opioid crisis. The underlying mechanism of over-prescription when secondary markets exist reflects the role uncertainty and risk attitude at play in influencing physician behavior. Our experiment provides the first evidence on the effects of eliminating secondary markets and offers an explanation for over-prescription behavior in the presence of a secondary market.

The remainder of the paper is organized as follows. Section 2 provides a brief literature review. Section 3 summarizes the theoretical framework. Section 4 describes the experiment design and the specific predictions. Section 5 reports the results. Section 6 discusses the results. Section 7 offers concluding remarks.

2 Literature Review

A large body of literature has explored how the epidemic emerged and pinned the hope of alleviating the opioid crisis on policies involving its key players. On the demand side, the critical players are opioid-seeking-patients. On the supply side, the key players include the FDA, pharmaceutical companies and physicians. This paper contributes to the literature on the behavior of patients and physicians in driving the opioid crisis and complements the work investigating how the interaction between the primary and secondary markets has complicated the problem of solving the crisis.

[2]A recent study by Kemel et al.(2021) shows that GP's risk attitudes are associated with their prescribing practices. Specifically, risk averse physicians make more lab tests prescriptions.

2.1 Patients' behavior

As the vulnerable victims and the "culprits" for the opioid crisis, patients who frequently use opioids have been studied at the earliest stages in attempts to summarize the attributes of opioid misusers (Ives et al. 2006; Lusted et al. 2013; Sullivan et al. 2010). Ives et al.(2006) found that those with self-reported misuse history of cocaine and alcohol have a higher risk of becoming opioid misusers. Likewise, patients at the bottom 20% of the income distribution face stress and despair and demonstrate a higher demand for prescription opioids (Thombs et al. 2020). For convenience, and to avoid switching cost, patients tent to repeatedly visit physicians with whom they are familiar. Likewise, patients' decisions about physicians are driven by the incentive for at least some level of quality treatment (Biørn and Godager 2010; Dixon et al. 1997). Although, quality usually stands for treatment effects from a health perspective, for the opioid-seeking patient, the aims are more complex.

Given that prescription opioids can not only reduce a patient's pain[3], but also release large amounts of dopamine that can be addictive, patients who are incentivized to reduce the pain and recover health are classified as medical drug users. Meanwhile, those who only aim to achieve euphoria (even at the expense of sacrificing their health) are non-medical users[4]. Schnell (2017) argued that privately held information about patients' incentives influences physicians' prescription behavior, particularly when there exists a secondary market where patients can seek opioids not only for their own use (for medical or non-medical purpose), but for resale profit in the secondary market. Schnell (2017) further discussed the fact that drug-addicted patients are more likely to be non-medical drug users. She further modeled the health impact of prescription opioids (legitimate incentive for the drug users) and identified that the health impact is increasing in pain at a decreasing rate. As a comparison, marginal utility of addiction is increasing with the number of past consumptions (Cawley and Ruhm 2011). Therefore, patients who are addicted and have a history of opioid use might be more prevalent than patients with severe pain who are only seeking opioids for the health benefits. Likewise, since addicted drug users typically demonstrate very high willingness to pay for opioids, these non-medical users bid up the price and further incentivize prescribed-drug-users to become suppliers in the secondary market, thereby promoting drug diversions.

Thus far, most of the previous literature has focused on intrinsic factors that shape drug users' behavior, and modeled the patients as the party with less information (about their own condition and treatment options) than the physician. However, Schnell (2017) modeled

[3]Although opioid prescriptions in one geographic market is usually standardized to contain a certain number of pills, the prescription can result in heterogenous treatment effects depending on the severity of the patient's sickness level.

[4]Drug-seeking behavior of medical users is encouraged, as their incentives align with the medications' intention, while the incentives of non-medical users do not.

patients as the party holding more private information under the context of opioid prescription and investigated how the existence of the secondary market and the retradeability of opioids could broaden patients' incentives, influence their behavior, and further alter physicians' decisions. To draw more insights from the experiment, our work departs from Schnell (2017), which relies on the key assumption of patients' optimal decisions to predict physicians' optimal decisions. Therefore, although our work is based on Schnell (2017), we allow patients to make non-optimal decisions and contribute to the literature on patient preferences, addiction features and the market's influence on their behavior. In designing and implementing a simple experiment, our behavioral data measures the secondary market's impact on different-profile patients' incentives and decisions, and validates the predictions raised by Schnell (2017).

2.2 Physicians' behavior

A more recent wave of studies has examined the behavior of physicians (Chandra et al. 2011) attributing opioid abuse to physician's over-prescription behaviors over time (Bohnert et al. 2011; Dart et al. 2015; Paulozzi and Ryan 2006). Although some physicians (Hirsch 2017) rationalize their over-prescription behavior as helping patients reduce pain, the potential adverse consequences of opioid tolerance and dependence due to excess supply are also commonly recognized. Unused prescription opioids due to over-prescriptions have also enabled drug diversion and further exacerbated the opioid crisis (Powell et al. 2020).

Wide heterogeneity is a feature of physicians' prescription patterns (Barnett et al. 2017). The difference can be partially explained by the training and information physicians receive (Ahomäki et al. 2020; Schnell and Currie 2018). Schnell and Currie (2018) explained the heterogeneity by observing physicians' medical school ranks. Their paper suggests that physicians receiving good training from top medical schools prescribe less opioids compared to those lacking such training. Ahomäki et al. (2020) found that when physicians were provided information reminding them to prescribe cautiously, less pills were dispensed. By sending physicians private information letters, physicians, particularly persistent high prescribers, were nudged to prescribe significantly less to new patients. Another paper (Meinhofer 2015) found that once private information about a patient's drug shopping history[5] was revealed, physicians' prescription efficiency increased significantly as a consequence of the reduced asymmetric information. Also, cultural-social-economical background influenced prescription practice and made physicians prescribe differently across countries and states (Jacobsen et al. 2007).

[5]Patients with a significant history of shopping for opioids signal an abuse danger or high addiction level.

The presence of other medical service providers (physicians or nurse practitioners (NPs)) also have behavioral effects on the physician (Alexander and Schnell 2019; Brosig-Koch et al. 2017; McMichael 2018). While competition can reduce overprovision and underprovision of treatment (Brosig-Koch et al. 2017), granting NPs the ability to prescribe independently decreases physicians' opioid prescriptions (McMichael 2018). Although the overall effect on the number of opioid prescriptions dispensed are mixed (Alexander and Schnell 2019; McMichael 2018)[6], the beneficial effect on population health by allowing NPs to prescribe is recognized.

Physicians' services are frequently associated with monetary rewards[7]. As a result, their behavior can be influenced by incentives to earn monetary payoffs and enhance patient health benefits. Brosig-Koch et al. (2016, 2020) found that (1) performance-pay mechanisms crowd out physicians' intrinsic motivation for providing high quality patient care[8]; and (2) fees for service payment systems distort physicians' behavior from the patient optimum. Seminal papers by Farley (1986), Ellis and McGuire (1990) incorporated patients' welfare into physicians' utility. Schnell (2017) included the dual incentives to build an economic model of physician behavior and facilitated our understanding behind physicians' over-prescribing behavior. The model assumes that physicians are influenced by dual incentives: they are concerned about the opioid-bestowed health impact on patients, while also seeking to earn more visit fees. Given that higher visit fees can only be earned through more prescriptions (in equilibrium), the paper indicates that physicians who place almost equal weight (preference) on the income and patients' well-being should optimally over-prescribe to maximize their utility.

As the internal factors driving physicians' behavior have been widely explored in the empirical and theoretical literatures, our paper builds upon Schnell (2017), which controls physician features to focus exclusively on the impact of external market structures. Although physicians in our experiment are played by non-medical students, it is well-documented that one can create financial incentives in the lab so that medical and non-medical students in the lab make decisions consistent with physicians in the field (Brosig-Koch et al. 2016).

[6] McMichael (2018) found that allowing NP to prescribe results in an overall decline of opioid prescriptions across suppliers; Alexander and Schnell (2019) found the opposite which shows a general increase in opioid prescriptions.

[7] Between 2014 and 2015, around one-seventh of the physicians in the United States received opioid-related gifts from pharmaceutical companies (Hollander et al. 2020).

[8] Also, as discussed earlier by Bénabou and Tirole(2003, 2006), pay-for-performance incentives can have unintended consequences for the intrinsic motivation of service providers in the public domain.

2.3 The secondary market and the primary market

Finally, this paper contributes to literature examining the interaction between the primary and secondary markets, which can escalate the risk of over-prescription. The welfare analysis and diversion effects of increased prescription opioids, which require tracking the drug from the primary market to the secondary market, are difficult to fully analyze. The only papers that have specifically analyzed the interaction between the two markets are Powell et al. (2020), Meinhofer (2018), and Schnell (2017). Powell et al. (2020) used the reform in the Medicare Prescription Drug Benefit Program (Part D)[9] as a window to examine misuse and mortality among the Medicare-ineligible population, implying a spillover effect on the secondary market when opioid supply was expanded. Meinhofer (2018) acknowledged the public health progression by reducing the legal supply of opioids, while pointing to the doubling price of oxycodone on the secondary market and a switching effect to heroin when legal supply was constrained. As a complement to these works analyzing the effects of policies targeting the legal supply, Schnell (2017) prioritized the policies on the secondary market and estimated how its presence and removal would influence the behavior of both patients and physicians on the primary market.

This paper, as the first to examine experimentally how the two markets interact and influence the behavior of patients and physicians, has an advantage over other theoretical works that cannot trace the whole reallocation process of prescribed opioids. In documenting the final drug-takers after observing the diversion process of the drug, the experiment captures the effects of prescription opioids more generally and provides direct evidence from human decisions on the impact of eliminating the secondary market. Our findings help us provide an important complement to the ongoing policy discussion over approaches to mitigating the opioid crisis.

3 Theoretical Framework

3.1 Model Setup

We develop a simple model of patient and physician behavior based on Schnell (2017). Our model is a simplified version of her model that can be implemented in the experimental laboratory. We focus on whether the presence of the secondary market can reduce prescriptions.

There are two markets for opioids: (1) a legal primary market; and (2) an illicit, secondary market. On the primary market, the physician j is assigned with $I \geq 2$ patients who need

[9]Part D increased opioid use in the 65+ population and led to a subsequent increase of opioid supply in states with a large share of misusers 65 and older.

opioids from her. The physician observes all the assigned patients' pain levels and decide whether to prescribe to each visiting patient by comparing the visiting patient's pain level with her prescription standard (measured in pain). All the patients who visit and have pain levels reaching the physician's pain standard for prescription are provided a one-unit prescription for opioids. On the secondary market, all the prescribed units can be reallocated by the patients through the 'prescribed' selling the drugs to the 'non-prescribed'.

There are I patients, indexed by $i \in \{1, \ldots, I\}$. Each patient i is painful at severity $\kappa_i \in \mathbb{R}^+$ and has a privately known euphoria level $\gamma_i \in \mathbb{R}$ towards opioids. The higher the pain level is, the higher the pain relief demand (denoted by the monetized health impact level[10] $h(\kappa_i) \in \mathbb{R}$) the patient has. By consuming the prescribed drugs, the patient i can receive the health impact plus the euphoria level; by selling the prescribed drugs, the patient i can receive the price of the drugs on the secondary market which is $p^{SM} \in \mathbb{R}^+$. The value of the prescribed drugs v_i thus can either be $v_i(consume) = h(\kappa_i) + \gamma_i$ or $v_i(sell) = p^{SM}$, depending on patient i's choice of whether to consume the drugs and his characteristics (κ_i, γ_i). The incentive of a patient seeking opioids from the physician is therefore either to reduce pain ($h(\kappa_i)>0$;$\gamma_i \leq 0$), or to gain euphoria ($\gamma_i > 0$; $h(\kappa_i) \leq 0$), or to satisfy both demands of pain relief and euphoria ($h(\kappa_i) > 0$; $\gamma_i > 0$), or to earn profit by reselling at p^{SM}. Since the euphoria level of the patient (γ_i) is a private information, the value of the drugs to patient i and the true incentive of each patient, when visiting, cannot be identified by the physician.

Our model builds four ordered sickness level patients: sick0, sick1, sick2, sick3 that represent four discrete pain levels: $k_{sick0}, k_{sick1}, k_{sick2}, \ k_{sick3}$. Similarly, we build four ordered enjoyment levels: enjoy0, enjoy1, enjoy2, enjoy3 that represent the four discrete euphoria levels $\gamma_{enjoy0}, \gamma_{enjoy1}, \gamma_{enjoy2}, \gamma_{enjoy3}$. Given that each patient's profile (k_i, γ_i) is only self-observable, the physician and patients can only hold the belief of T different profiles of patients with T in the range of [4, 16][11].

The physician, in both cases, after observing the I patients' pain levels, sets a prescription threshold $k_j \in K$ to make patients with pain levels $k_i \geq k_j$ eligible for prescription. The threshold choice set of a physician is $K = \{\kappa_{sick0}, \kappa_{sick1}, \kappa_{sick2}, \kappa_{sick3}, \kappa_{sick3+}\}$, where '$\kappa_{sick0}$' represents the most lenient standard, offering every patient eligibility, and 'κ_{sick3+}' is the strictest standard, which results in prescribing to no one. To simplify the symbols, the thresholds of $sick0$, $sick1$, $sick2$, $sick3$, $sick3+$ represents $\{\kappa_{sick0}, \kappa_{sick1}, \kappa_{sick2}, \kappa_{sick3}, \kappa_{sick3+}\}$ in this paper.

[10] The function $h(\kappa)$ is assumed to be the same for all patients, monotonically increasing and concave. The estimated health function uses the one in Schnell(2017) and is $h(\kappa) = 684.72 \cdot In(0.66 \cdot \kappa + 0.012)$.

[11] If the patients' characteristics differ in either dimensions: {sick0, sick1, sick2, sick3, sick4} $\times$ {enjoy0, enjoy1, enjoy2, enjoy3}, there are 16 different profiles of patients. If each pain level is paired with a unique euphoria level, there are 4 different profiles of patients differing in both dimensions.

By prescribing to each visiting patient, the physician earns one unit of visit fee[12] $R_j \in \mathbb{R}^+$ and a weighted monetized health impact bestowed by the prescription decision: $\beta_j \cdot h(\kappa_i)$, where $\beta_j \in \mathbb{R}^+$ is the weight the physician places on her prescription bestowed population health impact relative to the visit fees. Without the secondary market, the health impact of one unit prescription is the prescribed patient's received health impact, whereas in the case with the secondary market, the health impact of the prescription depends on who eventually consumes it. The final drug consumers could either be the prescribed patient or the non-prescribed health-harming patient who buys.

The utility of the physician in the two cases is represented in equation (7) and equation (8), such that it is always the sum of two parts: the total visit fee collected by making N_j units of prescriptions, and the population health impact part which is the sum of the health impacts received by the N_j number of final drug consumers. Since the physician's optimal decision is deprived conditional on knowing which pain level patients' optimal decision is to consume, we will first discuss the optimal decisions of the patients before reaching the predictions of the physician's prescription decisions in the two cases.

Assuming that each patient knows whether he can be prescribed (see Table 1 for information set of each patient and physician and see Table 2 for key assumptions). Each patient has a non-binding budget constraint in both cases.

With the utility of the patient being the value associated with his action a_i: $v_i(a_i)$, minus the cost associated with his action a_i: $c_i(a_i)$, the task of the patient in both cases is to choose the optimal decision $a_i{}^*$ such that the utility is maximized ($a_i{}^* = arg\ max\ v_i(a_i)$ - $c_i(a_i)$). In the case without the secondary market (NSM), the only choice of $A_i^{NSM} = \{visit,\ not\ visit\}$ is equivalent to choosing from $A_i^{NSM} = \{consume,\ not\ consume\}$ since the only value of visiting the physician is the value of consuming the drugs. The cost of getting the prescription is a visit cost c^v, and a drug fee c^d. A pain eligible patient's problem in NSM is therefore to choose from $A_i^{NSM}(\kappa_i \geq \kappa_j) = \{consume,\ not\ consume\}$ to max $\{h(\kappa_i) + \gamma_i - c^v - c^d, 0\}$.

The optimal behavior of the patients in the NSM case $\alpha_i^{*NSM} \in A_i^{NSM}$ is therefore characterized by:

$$\alpha_i^{*NSM} = consume,\ if\ h(\kappa_i) + \gamma_i \geq c^v + c^d \textbf{ and } \kappa_i \geq\ \kappa_j \tag{1}$$

$$\alpha_i^{*NSM} = not\ consume, if\ h(\kappa_i) + \gamma_i < c^v + c^d \textbf{ or } \kappa_i < \kappa_j \tag{2}$$

[12]The visit fee collected by the physician is similar to a capitated payment system – the greater the number of patients treated by a physician, the greater the visit fees the physician receives (for an overview see, e.g., Iversen and Lurås 2006). In this paper, the more patients being prescribed, the more visit fees the physician can receive in the long term.

In the case with a secondary market (SM), due to the profitable selling opportunity (p^{SM} $> c^v + c^d$), all patients with the eligibility of being prescribed *visit* the physician, and either *consume* or *sell* on the secondary market; for patients with non-eligibility, their optimal choice is to *not visit* and then decide on the secondary market of whether to *consume by buy* or *do nothing*. The patient's decision problem with the secondary market is therefore summarized as to choose from $A_i^{SM}(\kappa_i \geq \kappa_j)$ = visit $\times$ $\{consume, sell\}$ for pain eligible patients to max ($h(\kappa_i) + \gamma_i - c^v - c^d$, $p^{SM} - c^v - c^d$) ; and to choose from $A_i^{SM}(\kappa_i < \kappa_j)$ = not visit $\times$ $\{consume\ by\ buy,\ do\ nothing\}$ for non-eligible patients to max ($h(\kappa_i) + \gamma_i - p^{SM}$, 0). The market clears under equilibrium on the secondary market.

In the SM case, the optimal behavior of pain eligible patients α_i^{*SM} $(\kappa_i \geq \kappa_j) \in A_i^{SM}$ is characterized by:

$$\alpha_i^{*SM}(\kappa_i \geq \kappa_j) = \arg\max(h(\kappa_i) + \gamma_i,\ p^{SM}) = \{visit \times consume\}, \tag{3}$$

$$\text{if } h(\kappa_i) + \gamma_i \geq p^{SM}$$

$$\alpha_i^{*SM}(\kappa_i \geq \kappa_j) = \arg\max(h(\kappa_i) + \gamma_i,\ p^{SM}) = \{visit \times sell\}, \tag{4}$$

$$\text{if } h(\kappa_i) + \gamma_i < p^{SM}$$

In the SM case, the optimal behavior of pain non - eligible patients α_i^{*SM} $(\kappa_i < \kappa_j) \in A_i^{SM}$ is characterized by:

$$\alpha_i^{*SM}(\kappa_i < \kappa_j) = \arg\max(h(\kappa_i) + \gamma_i - p^{SM}, 0) = \{not\ visit \times consume\ by\ buy\}, \tag{5}$$

$$\text{if } h(\kappa_i) + \gamma_i \geq p^{SM}$$

$$\alpha_i^{*SM}(\kappa_i < \kappa_j) = \arg\max(h(\kappa_i) + \gamma_i - p^{SM}, 0) = \{not\ visit \times do\ nothing\}, \tag{6}$$

$$\text{if } h(\kappa_i) + \gamma_i < p^{SM}$$

Given the conditions of the optimal visit decisions in NSM (equation (1)) and the optimal visit decisions in SM (equations (3) and (4) regardless whether the patient has the incentive to consume), more visiting patients should be expected in SM than in NSM due to the profitable reselling opportunity.

Given that patients with $\alpha_i^* = consume$ (either prescribed or buy) are those with $h(\kappa_i)$ $+ \gamma_i \geq p^{SM}$ in SM (equations (3) and (5)) and those with $h(\kappa_i) + \gamma_i \geq c^v + c^d$ in NSM (equation (1)), and that $p^{SM} > c^v + c^d$, the eligible patients with $h(\kappa_i) + \gamma_i$ in the range of $[c^v + c^d, p^{SM})$ change their optimal decision from $\alpha_i^{*NSM} = consume$ to $\alpha_i^{*SM} = sell$ and sell the prescribed drugs to those non-eligible euphoria driven buyers ($\gamma_i > 0$; $h(\kappa_i) < 0$) with $h(\kappa_i) + \gamma_i \geq p^{SM}$.

The presence of the secondary market, by changing the final drug consumers (patients with $\alpha_i^* = consume$) given the same prescription standard, influences the physician's decisions. As each physician concerns about the population health impact bestowed by her N_j units of prescriptions, which is the sum of the health impacts received by the N_j number of final drug consumers ($\sum_{i=1}^{N_j} h(\kappa_i)$). Besides, the population health concern the physician has is $\beta_j \in \mathbb{R}^+$ times her concern over the office visit revenue ($N_j \cdot R_j$).

According to the information given to the physician (Table 1) and the key assumptions (Table 2), the general format of a physician's utility in both cases is:

$$u_j(\kappa_j,\ \alpha_i^*) = N_j(k_j, \alpha_i^*)R_j + \beta_j \sum_{i=1}^{N_j} h(\kappa_i) \tag{7}$$

where $N_j(\kappa_j, \alpha_i^*)$ is the number of patients whose optimal decision α_i^* in the primary market is to *visit* the physician in both cases given the threshold of κ_j; $\beta_j \sum_{i=1}^{N_j} h(\kappa_i) \in \mathbb{R}$ is the utility that the physician derives from the total health impact her prescription bestowed to the patients, whose optimal decision α_i^* is *consume* eventually under the threshold κ_j. β_j mirrors the importance of population health to physician j. Considering the possibility of drug diversions in the SM case, if there are m out of the N_j prescribed patients whose optimal decision is $\alpha_i^{*SM} = \{visit \times sell\}$, the physician's derived utility from the population health impact becomes: $\beta_j(\sum_{i=1}^{N_j - m} h(\kappa_i) + m\ \bar{h}^{SM})$, where $\bar{h}^{SM}$ is the average health impact of the buyers on the secondary market when the threshold is κ_j. The utility function in the SM case then becomes (8), which captures the change in the population health due to drug diversions.

$$u_j(\kappa_j, \alpha_i^*) = N_j(\kappa_j,\ a_i^*)R_j + \beta_j(\sum_{i=1}^{N_j - m} h(k_i) + m\ \bar{h}^{SM}) \tag{8}$$

Table 1: Information set of each agent in the model

Agent	Information
All (Common knowledge)	• I Patients with four discrete pain levels and four discrete euphoria levels $\{\kappa_i,\ \gamma_i\} = \{(\kappa_{sick0},\ \kappa_{sick1},\ \kappa_{sick2},\ \kappa_{sick3}) \times (\gamma_{enjoy0},\ \gamma_{enjoy1},\ \gamma_{enjoy2},\ \gamma_{enjoy3})\}$ • The value of consuming the drug, $v_i(\alpha_i = consume)$: Pain relief + euphoria level = $h(\kappa_i) + \gamma_i$ • The value to sell the drugs ($v_i(\alpha_i = sell)$: p^{SM} • The cost to consume the drugs ◊ on the primary market: the visit cost + the drug fee = c^v+c^d ◊ on the secondary market: the cost to obtain the drugs: p^{SM} • Physician's profile $\{R_j,\ \beta_j\}$ • Physician's threshold decision κ_j (only known under equilibrium)
Patient (Private information)	• Patient's taste level γ_i
Physician	• I Patients' pain level distribution: $\{\kappa_i\text{: } i = 1,2,3\ldots I\}$

Table 2: Key assumptions of the theory

• The pain level and the euphoria level of a patient i are independent
• β_j is constant for physician j: physician's weight towards patients' health is the same for the buyer patients and prescribed patients.
• Patient behave optimally as a_i^* to maximize $u_i(a_i \vert\ k_j)$ and a_i^* (especially those with a_i^* = *consume* under each threshold) is used to derive the equilibrium threshold decision of the physician, κ_j^*.

3.2 Model Solution

The optimal prescription threshold κ_j^* for both market structures under patients' optimal decision α_i^* is given by

$$\kappa_j^* = \arg\max\ u_j(\kappa_j, \alpha_i^*) \tag{9}$$

We are interested in comparing different market structures with respect to optimal prescription thresholds. For this, we consider a physician j with given characteristics of revenue R_j and altruism level β_j and a certain profile distribution of I patients. Among the I patients, the extended resale opportunity in the SM case induces the heterogeneous-profiles patients to have differed incentives to visit (sell/consume). Therefore, even given the same threshold κ_j, α_i^* of the I patients could differ in SM as compared to that in NSM. Such change of the patients' optimal behavior, in turn changes the optimal solutions of the physician's prescription threshold.

In both the NSM case and the SM case, the optimal prescription threshold κ_j^* should make the marginal utility of prescribing to the patient at the equilibrium threshold level equal 0.

Therefore, in the NSM case, the equilibrium threshold κ_j^{*NSM} should make equation (10) hold:

$$R_j + \beta_j \; h(\kappa_j^{*NSM}) = 0 \tag{10}$$

Intuitively, this means that in equilibrium, the marginal revenue earned when prescribing to the patient at the equilibrium threshold pain level κ_j^{*NSM} in the NSM case offsets the weighted health harm bestowed to the marginal prescribed patient i with pain level $\kappa_i = \kappa_j^{*NSM}$.

Similarly, in the SM case, κ_j^{*SM} satisfies:

$$R_j + \beta_j \left(\frac{N_j - m}{N_j} \; h(\kappa_j^{*SM}) + \; \frac{m}{N_j} \; \bar{h}^{SM} \right) = 0 \tag{11}$$

Given that (10) = (11) = 0 and that the average health impact on the secondary market $\bar{h}^{SM}$ is smaller than the health impact at κ_j^{*NSM}, the equality would only hold if $\kappa_j^{*SM} > \kappa_j^{*NSM}$.

Under our theoretical framework, in each case, it is sufficient to consider and compare the utility outcomes of physicians at each threshold level: $u_j(\kappa_j = \kappa_{sick0}, \alpha_i^*)$, $u_j(\kappa_j = \kappa_{sick1}, \alpha_i^*)$, $u_j(\kappa_j = \kappa_{sick2}, \alpha_i^*)$ $u_j(\kappa_j = \kappa_{sick3}, \alpha_i^*)$, $u_j(\kappa_j = \kappa_{sick3+}, \; \alpha_i^*)$ to draw the equilibrium threshold κ_j^{*NSM} and κ_j^{*SM}

$$\begin{aligned} \kappa_j^{*NSM} = &\arg\max \Big(u_j^{NSM}(\kappa_j = \kappa_{sick0}, \alpha_i^*), u_j^{NSM}(\kappa_j = \kappa_{sick1}, \alpha_i^*), \\ & u_j^{NSM}(\kappa_j = \kappa_{sick2}, \alpha_i^*), u_j^{NSM}(\kappa_j = \kappa_{sick3}, \alpha_i^*), 0 \Big) \end{aligned} \tag{12}$$

$$\begin{aligned} \kappa_j^{*SM} = &\arg\max \Big(u_j^{SM}(\kappa_j = \kappa_{sick0}, \alpha_i^*), u_j^{SM}(\kappa_j = \kappa_{sick1}, \alpha_i^*), \\ & u_j^{SM}(\kappa_j = \kappa_{sick2}, \alpha_i^*), u_j^{SM}(\kappa_j = \kappa_{sick3}, \alpha_i^*), 0 \Big) \end{aligned} \tag{13}$$

Note: since the payoff of both the physician and patients is 0 when the threshold is κ_{sick3+}, $u_j(k_j = \kappa_{sick3+}, \; a_i^*)$ is substituted by 0 in the bracket of (12) and (13).

3.3 Parameters and theory predictions

Given the four levels of sickness severity and four levels of enjoyment towards opioids, there could be at most 16 types of heterogeneous profile patients in our model. However, since the exact patient types (κ_i, γ_i) are confidential, four types of patients are sufficient to simplify the model, while fully representing the possible incentives behind a patient's behavior in the

SM case. The key is to pair each patient sickness level with a unique enjoyment level that differentiate their incentives in the SM case of this model.

The four types of patients are [sick0, enjoy3], [sick1, enjoy1], [sick2, enjoy0] and [sick3, enjoy2]. While sick3 patients are given the severest sickness level, sick0 patients are given the highest taste level - enjoy3, so that sick0 and sick3 patients are both motivated to consume in both cases. Given the mediocre enjoyment levels with $h(\kappa_i) + \gamma_i < p^{SM}$, sick1 and sick2 patients, if eligible for prescription, change their visit intention from *consume* in the NSM case to *sell* in the SM case. Table 3 summarizes the parameters of the patients and their exact profile distributions.

Table 3: Experiment parameters of the patients: sickness levels and the associated health impacts, enjoyment levels and the number of patients of each type

Number of patients with each profile ($I = 24$)	Pain levels	Health impact	Enjoyment levels
I_{sick0} 8	κ_{sick0} 0.94	h_{sick0} -314	γ_{enjoy3} 1000
I_{sick1} 4	κ_{sick1} 1.4	h_{sick1} -45	γ_{enjoy1} 165
I_{sick2} 4	κ_{sick2} 1.7	h_{sick2} 86	γ_{enjoy0} 50
I_{sick3} 8	κ_{sick3} 2.5	h_{sick3} 348	γ_{enjoy2} 250

Notes: Each row represents the profile (κ_i, γ_i) of the patients with identical sickness level. The same sickness level patients, if consuming, receives identical points which are $h(\kappa_i)$ $+\gamma_i$.

3.3.1 Theory predictions under complete information

In the NSM case, given the cost parameters on the primary market: $c^v = 103$, $c^d = 15$, we have $u_i^{NSM}(\alpha_i = consume) > 0$ for all the patients. If the patients know whether they can be prescribed, the optimal behavior of the 24 patients characterized by equations (1) and (2) are therefore $\alpha_i^{*NSM}(\kappa_i \geq \kappa_j)$= *visit (consume)*; $\alpha_i^{*NSM}(\kappa_i < \kappa_j)$= *not visit (not consume)* under this setup. Given that the profile of the physician is $R_j = 103$ points, $\beta_j = 1.1$ and that $\alpha_i^{*NSM}(\kappa_i \geq \kappa_j)$= *consume*, the equilibrium threshold κ_j^{*NSM} that solves equation (12) is *sick1*.

In the SM case, given that the parameters of the price on the secondary market is $p^{SM} = 550 > c^v + c^d$ and due to the resale opportunity, the optimal decision of all the patients on the primary market is to *visit* the physician as long as $\kappa_i \geq \kappa_j$; however, not all patients consume even if prescribed. The solution for equation (13) is no longer *sick1*, but $sick3$, due to the changing optimal decisions of patients of sick1 and sick2 in the SM case (α^{*SM}_{sick1} ($\kappa_{sick1} \geq \kappa_j$)= {visit × *sell*}; α^{*SM}_{sick2}($\kappa_{sick2} \geq \kappa_j$)= {visit × *sell*}). For example, if the prescription threshold in the SM case is *sick1*, α^{*SM}_{sick0} ={not visit × *consume by buy*}, $\alpha^{*SM}_{sick1} = \alpha^{*SM}_{sick2}$={visit × *sell*}, and α^{*SM}_{sick3} ={visit × *consume*}. Therefore, the drug diversions from the four sick1 and the four sick2 patients to the eight sick0 patients in the SM case when the threshold κ^{SM}_j is *sick1* removes *sick1* from being the solution for equation (13). A stricter prescription standard *sick3* becomes the equilibrium threshold in the SM case that solves equation (13). As seen in Appendix B-Figure B1, a physician's payment is highest when the threshold is *sick1* in NSM and the payment is highest when the threshold is *sick3* in SM[13].

3.3.2 Theory predictions under incomplete information

To verify the equilibrium threshold is $sick1$ in NSM and $sick3$ in SM with incomplete information under the parameters in Table 3, we calculate the expected payoff[14] of each sickness level patients choosing $\alpha_i = visit$, assuming that the patients do **not** know the threshold, but only hold the belief of each threshold (except $sick3+$) being equally likely[15]. In SM case, given that the expected payoff of all the sickness level patients choosing $\alpha^{SM}_i = visit$ is positive, the best response (BR) of the patients in SM is $\alpha^{BR}_i(SM) = visit$. The theory predicted threshold given $\alpha^{BR}_i(SM) = visit$ in SM is still $sick3$, same as the solution for equation (13).

In NSM case, due to the negative expected payoff of sick1 and sick2 patients choosing $\alpha^{NSM}_i = visit$, and the positive expected payoff of sick0 and sick3 patients choosing $\alpha^{NSM}_i = visit$, $\alpha^{BR}_{sick1}(NSM) = \alpha^{BR}_{sick2}(NSM) = not\ visit$, $\alpha^{BR}_{sick0}(NSM) = \alpha^{BR}_{sick3}(NSM) = visit$.

[13] Our model allows us to compare prescription threshold levels for specific market structures under equilibrium. Such theory predictions, however, are based on assumptions that the visit intention of the patients can be fully anticipated by the physician and that the patients know the threshold and can best response to each threshold. Therefore, we also predicted the behavior of the patients under incomplete information regarding the prescription threshold. The model under both complete and incomplete information settings predicts a stricter prescription threshold in the case with the secondary market than not. Our experiment, without fully revealing the visit intention of the patient or the threshold, however, shows that the presence of the secondary market demotivates physicians to be stricter in prescribing.

[14] See Appendix B figure B2 for detailed information about the expected payoffs of the patients choosing *visit* in the two cases.

[15] Threshold of $sick3+$ should not be considered as a possible threshold for both the patients and the physician as it results in zero payoff for both the patients and the physician and this is known by all the subjects. A natural belief a patient with incomplete information hold regarding the likelihood of each threshold is: $Prob(sick0) = Prob(sick1) = Prob(sick2) = Prob(sick3) = 1/4$

Based upon this, the equilibrium thresholds for the physician in NSM, $\kappa_j^{*NSM} \in \{sick1, sick2, sick3\}$[16] Among the three best response thresholds in NSM, however, $sick1$ is the weakly dominate one given that the patients of sick1 and sick2 could deviate from the best response and choose $\alpha_i^{NSM} = visit$. The theory predicted threshold in NSM under incomplete information is still $sick1$, same as the solution for equation (12).

3.4 Hypotheses

Based on the predictions regarding the behavior of the patients and the physician, we first derive two hypotheses to test in the experiment. Our hypotheses all deal with the effect the presence of the secondary market may induce.

The first hypothesis relates to the prescription behavior of the physician. Due to the drug diversions that would be triggered by prescription thresholds of $sick1$ and $sick2$ in the SM case, a stricter prescription threshold should be anticipated in the SM case than in the NSM case[17].

Hypothesis 1 *The physician sets a stricter prescription threshold in the case of SM than in the case of NSM.*

Hypothesis 1a *In NSM, prescription threshold of sick1 is chosen most frequently*

Hypothesis 1b *In SM, prescription threshold sick3 is chosen most frequently*

The second hypothesis relates to the behavior of the patients. Due to the profitability of selling drugs on the secondary market, the expected payoff of the sick1 and sick2 patients visiting the physician is negative in NSM and positive in SM [18]. Theoretically, we should expect more visitors in SM than in NSM and it can be summarized as follows:

Hypothesis 2 *The patients visit the physician more frequently in the SM case than in the NSM case.*

According to the optimal decisions of the patients at each threshold level in the SM case, the third hypothesis relates to the number of drug diversions[19] when each threshold is reached, and is summarized as follows:

[16] Given that the patients of sick1 and sick2 will not visit the physician in NSM, the payoff of the physician setting the threshold as $sick1$ is the same as choosing the threshold of $sick2$ or $sick3$ in NSM.

[17] See Appendix B figure B1 and figure B3 for detailed information about the maximal payoffs of the physician, setting different thresholds in each case.

[18] See Appendix B figure B2 for detailed information about the expected payoffs of the patients choosing *visit* in the two cases.

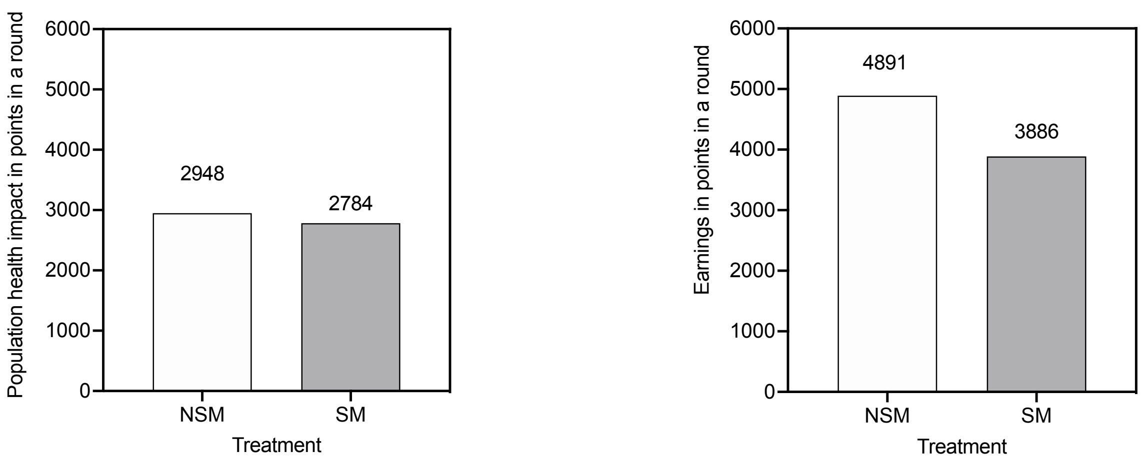
[19] The deviation from the theory predicted drug diversions at each threshold level can lead physician subjects to form wrong beliefs about how each threshold could trigger drug diversions. The number of drug diversions are closely related to the physician's round payoffs and the round population health impact in SM.

Hypothesis 3 *The number of drug diversions differs at different prescription thresholds, with sick1 triggering the maximal number of drug diversions. Sick2 is expected to trigger the second highest number of drug diversions. And thresholds of sick3 and sick0 result in no drug diversion.*

Based on the optimal behavior of the patients and physician, we calculate the population health impact, which is the sum of the individual health impact of those final drug consumers among the I patients (Figure 1(a)). We also calculate the social welfare, which is the expected earnings of physician (Figure 1(b)) and each type of patient (Figure 2) in each case. Our calculation indicates that both the population health impact and the social welfare is lower in the SM case than in the NSM case. This is summarized in the following two hypotheses:

Hypothesis 4 *The population health impact is lower in the case of SM than in the case of NSM.*

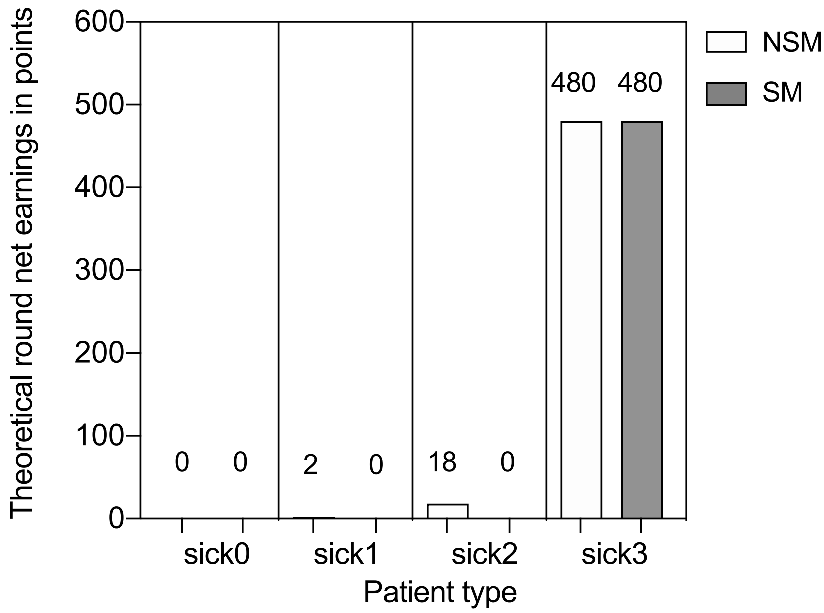
Hypothesis 5 *The social welfare of both patients and physician are lower in the case of SM than in the case without the secondary market.*



(a) Population health impact (b) Social welfare of the physician

Notes: In Figure (a), each predicted population health impact is calculated by assuming the equilibrium thresholds are chosen and patients are behaving optimally in each treatment. Same assumptions are made when calculating the social welfare of the physician in Figure (b).

Figure 1: Theoretical (a) Population health impact and (b) Social welfare of the physician in the two cases



Notes: Only patients of sick1 and sick2 are slightly better off in NSM than in SM when each player is behaving optimally.

Figure 2: Theoretical social welfare of patients given the threshold of $sick1$ in NSM, and the threshold of $sick3$ in SM

Given the uncertainty about how physicians' prescription decisions could affect public health consequences, particularly when there is a secondary market such that resell options are available, we might expect risk attitudes to influence physicians' prescription decisions, especially in SM.

If the case with the secondary market does not have extra uncertainty compared to the case without the secondary market, the null hypotheses below regarding uncertainty, risk aversion and physicians' prescription behavior should be true.

Hypothesis 6 *For the same threshold decision-makers, risk-attitudes are uniformly distributed across treatments.*

Hypothesis 6a *risk aversion distribution of physician subjects setting threshold as* $sick0 \cup sick1$ *in NSM = risk aversion distribution of physician subjects setting threshold as* $sick0 \cup sick1$ *in SM*

Hypothesis 6b *risk aversion distribution for physician subjects setting threshold as* $sick2 \cup sick3$ *in NSM = risk aversion distribution for physician subjects setting threshold as* $sick2 \cup sick3$ *in SM*

4 Experiment Design

We employ a two-treatment-between-subject design to test the above hypotheses. The two treatments differ according whether the secondary market is present. We refer to our treatments as: treatment without the secondary market (NSM); and treatment with the secondary market (SM).

Before the experiment began, subjects were given instructions for the first part of the experiment - a drug prescription game[20], which were also read aloud by the experimenter. After subjects finished reading the instructions and completed the comprehensive quiz successfully, they proceeded to the drug prescription game, which was the most important part of our experiment.

The drug prescription game consisted of 30 rounds. Subjects were assigned to be the patients of type sick0, sick1, sick2 or sick3 or the physician. Patients were each given an endowment of 653 points. In each round, the roles were randomly re-assigned. Subjects observed their profile and all possible payoffs at the beginning of the round[21]. Then, each patient subject first decided whether to "visit" or "not visit" in the primary market stage before answering a 7-likert scale question about their likelihood of being prescribed. Simultaneously, the physician made the threshold decision after observing the sickness level distribution of the I patients, the physician's own profile $\{R_j,\ \beta_j\}$ and the different set of possible payoffs[22] linked to each threshold decision. In contrast to the theoretical framework, the patients making the visiting decision knew nothing about the prescription threshold in round t, $\kappa_{j,t}$, or the subject identity of the physician. After all the subjects made their choices, each patient knew whether they had been prescribed. The patients who chose "visit" knew whether their sickness level reached the threshold, while patients who chose "not visit" opted out of the opportunity to learn this information in the feedback page. The physician was informed of the number of "visit" patients at each sickness level, the sickness levels of the prescribed patients (visiting patients with $\kappa_i \geq \kappa_{j,t}$) and the patients who

[20]See Appendix A in details.

[21]Each patient was given a table of possible payoffs. The table in display reflected patient i's six possible payoffs when the patient chose their sickness level from a dropdown menu of sick0, sick1, sick2, sick3 and their enjoyment level from another dropdown menu of enjoy0, enjoy1, enjoy2, enjoy3. The table changed dynamically when a different profile was chosen. Learning the payoff tables of other possible profile patients (15 other tables) did not help the decision making of patient i.

[22]The physician tentatively chose thresholds from a dropdown menu to learn the set of possible payoffs when choosing each threshold. The table changed dynamically when different thresholds were chosen (five tables in total: table of $sick0$ as the threshold, table of $sick1$ as the threshold, table of $sick2$ as the threshold, table of $sick3$ as the threshold and table of *more severe than* $sick3$ as the threshold).

eventually consumed the drugs[23].

In NSM, the feedback page at the end of the primary market included the round utility of all individuals, as this was the end of the experiment in a round. In SM, the experiment proceeded after the revelation of the prescription result to the patients. Based on the prescription result, the prescribed patients were given the option to "consume" or "sell" and the patients without prescriptions were given the option to "buy" or "do nothing" on the secondary market. The submitted "buy" and "sell" orders would all succeed only if an equal number of buyers and sellers are present[24]. The physician was in the waiting page while the patients were making their decisions on the secondary market. After all the patient subjects made their choices, the physician was notified of the sickness levels of the final prescription receivers and the physician's round utility. The physician was also informed of the initially visiting patients' sickness levels and the initially prescribed patients' sickness levels, so that the physician could track the drug diversions following the physician's prescription decision. The patients were notified of the transaction result and their round end utility. In both treatments, participants engaged in all 30 rounds (four practice rounds, followed by 26 real rounds) following the procedure mentioned above.

After all subjects completed the prescription game, they were asked to complete part 2 of the experiment - a loss-aversion task (Gächter et al. 2007) and part 3 of the experiment - a risk-aversion task (Holt and Laury 2002), followed by a short demographic questionnaire. When all subjects finished these parts, they were paid in cash privately. The payment is a random-chosen-round's (5th-30th rounds) payment of the drug prescription game and the earnings from the loss aversion task and the risk aversion task.

5 Results

5.1 Overview of the experiments

The experiments were programmed in oTree (Chen et al. 2016). We conducted all experiments at George Mason University, from October 2019 to February 2020. 200 students participated in our experiments (100 subjects in each treatment). The experiments lasted for about two and a half hours. Subjects could earn \$23.66 (including the \$5 show-up fees

[23]In NSM, the eventual drug takers are exactly the patients who were prescribed; in SM, they are not necessarily the prescribed patients and the feedback page to the physician was displayed after the transactions on the SM was completed.

[24]If the number of the buyers and sellers on the secondary market is not equal, then not all buyers and sellers will be able to transact successfully. For example, if there are five sellers and three buyers then all three buyers can purchase the drug, while two sellers would not be able to sell, and similarly if there were more buyers than sellers.

and \$5 participation fee) on average.

We drop the four practice rounds from our analysis; therefore, all statistical tests use only data from rounds 5 - 30. Table 4 summarizes the sample size of the key variables. Table 5 summarizes the sample characteristics in each treatment.

Table 4: Sample size of the key variables

Treatment	*NSM*	*SM*
Participants	100	100
Patients	sick0: 100 sick1: 100 sick2: 99 sick3: 100	sick0: 100 sick1: 99 sick2: 99 sick3: 100
Physicians	78	72
Incentivized rounds	26×4 sessions = 104	26×4 sessions = 104

Note: the key variables are the physicians' threshold decisions, patients' decisions, round population health impacts and each subject's average earnings as each type of patient. Due to complete randomization of role updating at each round, there are only 99 subjects who have played the role of sick2 patient in NSM and SM; similarly, there are only 99 subjects who have played the role of sick1 patient in SM.

Table 5: Sample characteristics in each treatment

	subjects in *NSM* (N = 100)		subjects in *SM* (N = 100)	
	Mean.	s.d.	Mean.	s.d.
Age	20.51	2.25	21.84	4.04
Female	0.53	0.50	0.52	0.50
Loss aversion	3.19	1.50	2.74	1.73
Risk aversion	5.60	1.88	5.36	2.31

Note: each treatment's first session did not include a risk-aversion task, so only 75 subjects in each treatment had finished the risk aversion task. Other attributes account for 100 subjects in each treatment. Risk aversion is the number of non-risky choice(s) subjects made in the risk aversion task; Loss aversion is the number of lotteries subjects refused to play in the loss aversion task.

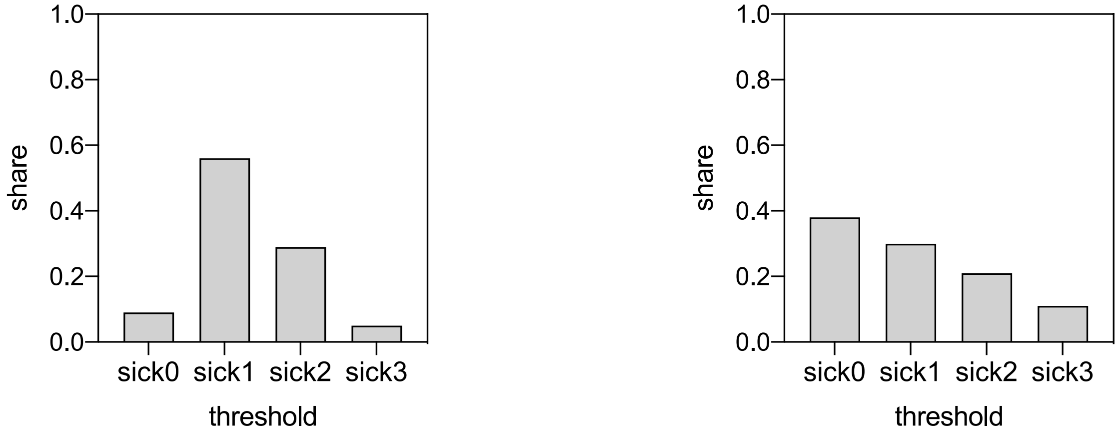
5.2 The physicians' prescription decisions

We first focus on the behavior of the physician, which includes their prescription threshold decisions in the two treatments.

We first look only at all the subjects' threshold decisions when playing the physician (N = 78 for NSM, N = 72 for SM) for the first time. The reason is to ensure that no learning effect is influencing their decisions. We later cluster the subjects playing physician for multiple rounds in each treatment (N = 22 for NSM, N = 21 for SM), so that we can verify our findings are robust even for non-first prescription decisions.

Figure 3 shows the share of subjects that chose each threshold when playing the physician for the first time in each treatment. Our results contradict the theory predictions obtained by Schnell (2017). In our experiment, subjects playing as physicians set the threshold lower in SM than in NSM, due to physician subjects' non-optimal decisions in the SM case.

Among the 78 subjects who were physician at least once in NSM, 44 chose $sick1$ as the threshold when playing the physician for the first time. This share of 56% is significantly above the 25% level suggested by randomization (binomial test, $p < .01$). Among the 72 subjects who played physician at least once in SM, 27 chose $sick0$ as the threshold when playing the physician for the first time, while the theory predicted threshold $sick3$ was chosen only by eight subjects. Therefore, the share of subjects choosing $sick0$ (38%) is significantly higher than the share of subjects choosing $sick3$ (11%) (binomial test, $p = 0.01$). The share of subjects choosing the predicted threshold $sick3$ in SM (11%) is significantly lower than 25% (binomial test, $p < 0.01$). For both treatments, the distribution of the share for ($sick0$, $sick1$, $sick2$, $sick3$) is significantly different from (25%, 25%, 25%, 25%) suggested by randomization (chi-square goodness of fit, $p < 0.01$).



(a) NSM (b) SM

Notes: there is one subject in SM who chose "*more severe than sick*3"(same as *sick*3+ in the model) when playing the physician for the first time. Since the threshold of "*more severe than sick*3" is known by all subjects as one that will lead to zero payments for both patients and physician, it is deemed as a mistake and is not counted in Figure 3(b). Figure 3(b) includes 71 subjects and Figure 3 (a) includes 78 subjects.

Figure 3: Proportion of subjects choosing each threshold in (a) NSM and (b) SM (when playing the physician for the first time)

By examining the behavior of the 22 multiple-round[25] - physician subjects in NSM and the behavior of the 21 multiple-round-physician subjects in SM, we find that even with switching decisions for subjects being a physician again in later rounds, our results regarding physician's prescription behavior in the two treatments are robust to the switching behavior[26].

Therefore, we reject Hypothesis 1, as the theory predicted threshold *sick*3 in SM is not dominantly chosen. This discrepancy can be supported by observing all the physician subjects' first-time threshold decisions and also through analyzing the behavior of the multiple-round-physician subjects. Our findings support the opposite of the supposition listed in Hypothesis 1, which indicates that the secondary market actually demotivated physicians to prescribe cautiously. This is our first result:

Result 1 *the theory predicted threshold sick1 is indeed chosen most frequently when the secondary market is absent, while the theory predicted threshold sick3 is not chosen frequently in the case with the secondary market. Relative to the prescription thresholds in NSM, physicians set lower thresholds in SM than in NSM, which leads to more prescriptions in the case with the secondary market.*

[25]The number of rounds these 22 subjects played as physician ranges from two to five.

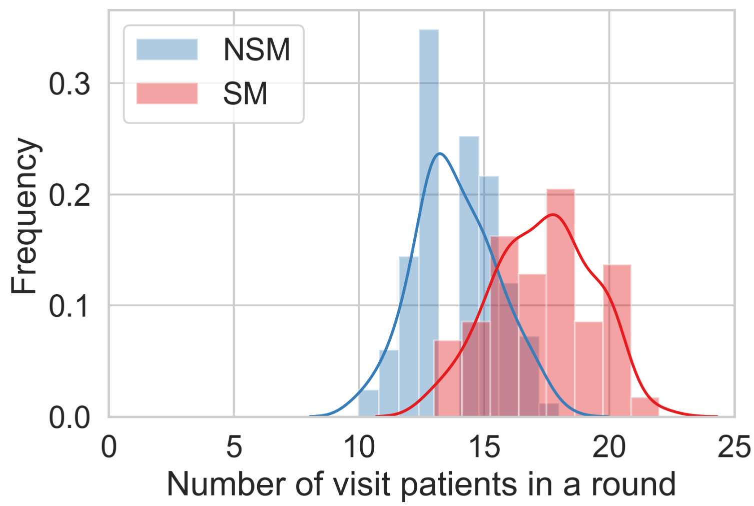
[26]For multiple-rounds physician subjects in NSM, the average frequency of choosing the theory predicted threshold *sick*1 is 62%. And for multiple-rounds physician subjects in SM, the average frequency of choosing the theory predicted threshold *sick*3 is only 13%.

5.3 Patients

In this section, we investigate the results from the point of view of patients. We first consider their decisions to visit the physician at the primary market. Then, we study the number of transactions made by patients when the secondary market is present.

5.3.1 Patients' visit decisions on the primary market

By comparing the 104 incentivized rounds in the two treatments, Figure 4 shows that the number of round visitors in SM is significantly higher than in NSM (t-test, $p < .01$). Our finding confirms the theory prediction regarding a higher visit rate when the secondary market is present.



Notes: Since each round has 24 patients, the maximal number of visitors in a round(x-axis) is 24. We focus on incentivized rounds (N = 104) and exclude 1-4 rounds of each session.

Figure 4: Histogram of number of visitors in a round

Our findings confirm Hypothesis 2, and our second result is:

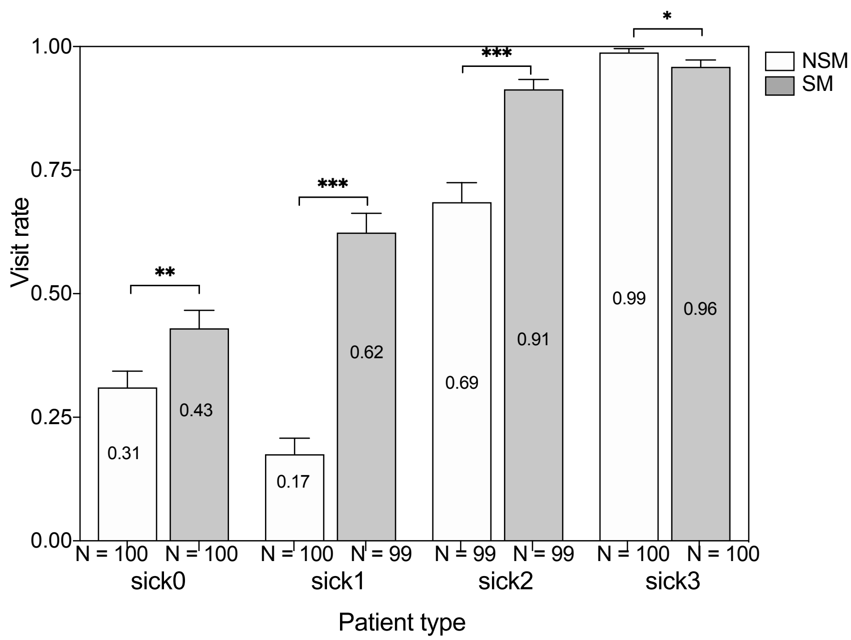
Result 2 *Patients visit the physician more frequently when the secondary market is present than when it is absent.*

We further analyzed the subjects' visit rate when playing each type of patient (Shown in Figure 5). Compared to the theory prediction that only sick1 and sick2 patients will visit the physician more frequently due to the resale opportunity in the SM[27], we also find that

[27]Theoretically, the resale opportunity should not influence the visit decision of the sick0 and sick3 patients, as their optimal behavior is to consume the drugs regardless of whether the secondary market is present.

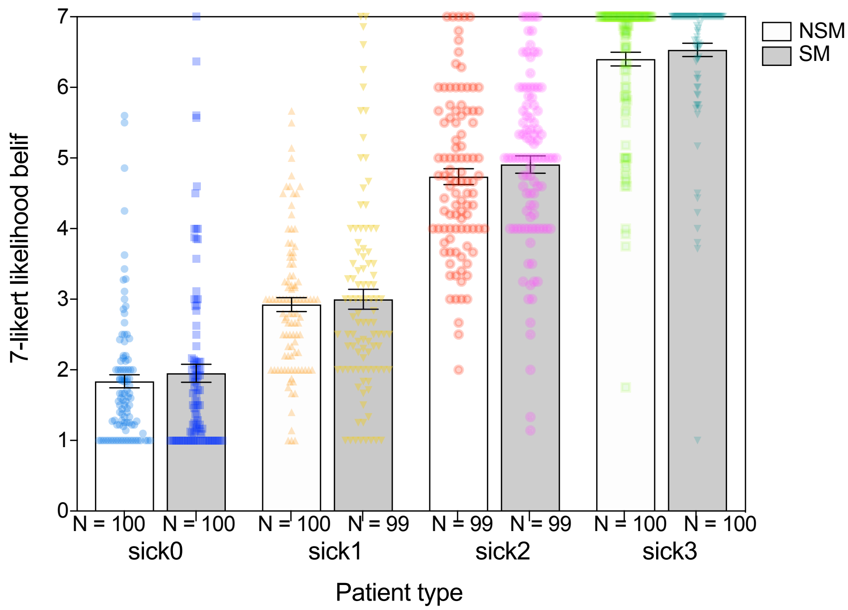
the visit rate of sick0 is significantly higher in SM than in NSM (t-value = -2.44, $p = 0.016 < 0.05$). Although one possible explanation is that sick0 patients in SM have higher confidence in getting prescribed than in NSM, the answers of the 7-likert question by subjects as sick0 in this experiment reject this hypothesized explanation. As shown by Figure 6, the average belief held by subjects being sick0 regarding the likelihood they can be prescribed is not significantly different across treatments (t-value = -0.73, $p = 0.23$).

Figure 5 and Figure 6 together show that within each treatment, although the visit rate is not always increasing with patients' sickness levels (e.g. in NSM), patients' beliefs about the likelihood of being prescribed increase with the severity of sickness levels.



Notes: Vertical black bars represent standard error of the mean (SEM). Each data point in each column is the average visit rate of a subject playing this patient type.
* $p < 0.1$, ** $p < 0.05$, ***, $p < 0.01$.

Figure 5: Average visit rate of subjects as each type of patient in the two treatments



Notes: Vertical black bars represent standard error of the mean (SEM). Each dot in each treatment represents the average belief of one subject as this sickness level patient (regarding the likelihood of being prescribed)

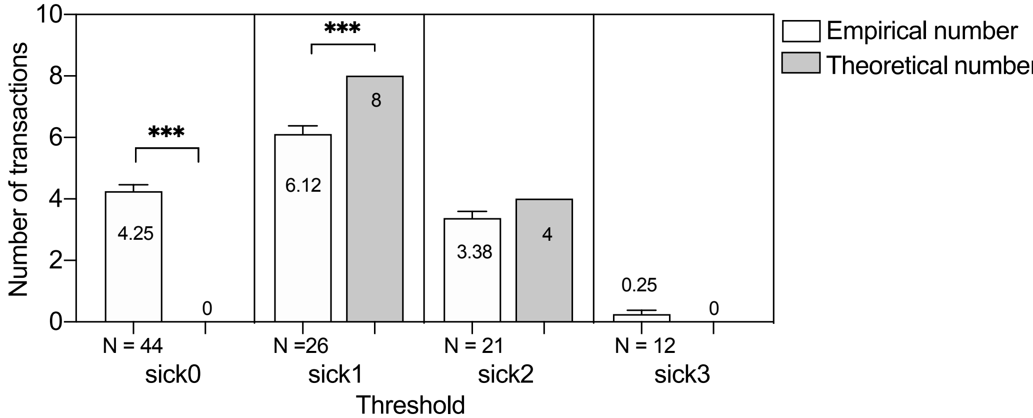
Figure 6: Average beliefs of the likelihood of being prescribed as each type of patient

5.3.2 The transaction results driven by patients' decisions on the secondary market

Based on our setup, if patients behave optimally, then each threshold level has an optimal number of drug diversions in SM, which is eight when the threshold is sick1, four when the threshold is sick2, and 0 when other thresholds are chosen[28].

By clustering the rounds each threshold is chosen in SM, shown by Figure 7, we find that the average number of transactions when *sick0* is chosen (4.25) is significantly higher than 0 (t-value = 20.38, p <.01) and the average number of transactions (6.12) when *sick1* is chosen is significantly less than 8 (t-value = -7.19. p <.01). The average number of transactions when the threshold is *sick2* or *sick3* is not significantly different from the theory predicted levels.

[28]Since our experiment gave feedback to the physicians at the end of each round, whether the number of drug diversions is consistent to the theory prediction is critical for the 21 multiple rounds physician subjects' non-first choice(s) in SM. Also, it plays an important role influencing the population health.



Notes: Vertical black bars represent standard error of the mean (SEM).
* $p < 0.1$, ** $p < 0.05$, ***, $p < 0.01$.

Figure 7: Average number of transactions when each threshold is chosen - a comparison between empirical and theoretical numbers

Therefore, our findings regarding patients' activities on the secondary market reject Hypothesis 3. Our third result is as follows:

Result 3 *Drug diversions are associated with the thresholds. The absolute number of drug diversions deviating from the theory predicted level is higher when the threshold is lower*[29]*, which means the more severe the over-prescription, the more unpredictable the number of drug diversions.*

The reason behind the higher than theory predicted number of transactions when the threshold is $sick0$ is that not all pain-eligible patients will visit in rounds when the threshold is $sick0$ (as shown in Figure 5, the average visit rate of subjects as sick0 patients in SM is only 43%). Those sick0 patients who could be prescribed (rounds when threshold is $sick0$) but did not visit turned to buyers and drove the transactions on the secondary market.

Even though the threshold of $sick0$ achieved higher than predicted drug diversions, we do not find a "patient' effect" on population health when the threshold is $sick0$. As shown in Figure 10 (a), the population health impact deviates from the theory predicted population health impact[30] and the deviation are all due to the physician[31]. Theoretically, the threshold of $sick0$ leads to the lowest population health outcome compared to the other thresholds.

[29]The number of transactions when threshold is $sick0$ is higher than predicted. Number of transactions when threshold is $sick1$ is lower than predicted. The number of transactions when physician does not over prescribe (threshold is $sick2$ or $sick3$) is similar to the predicted level.

[30]The theory predicted population health impact in SM is achieved when physician choose $sick3$ and patients best respond to it (behave as α_i^{*SM}).

[31]Detailed explanations are in Section 5.4.2.

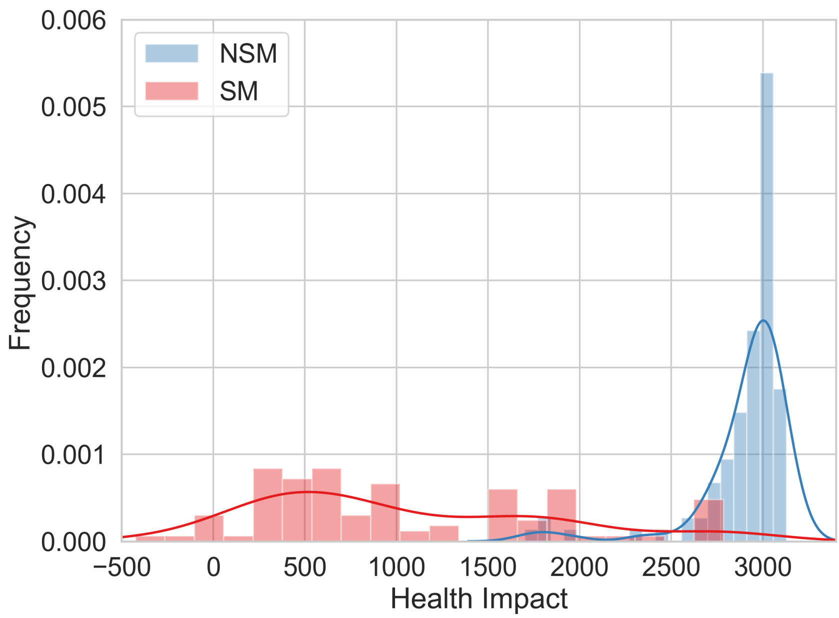
Empirically, the threshold of $sick0$ indeed contributed to the lowest observed population health outcome.

When the thresholds are $sick1$ and $sick2$, the insufficient transactions drive the health outcome to be better than the predicted levels (Figure 10(b), (c) – “patients’ effect”).

5.4 Population health impact

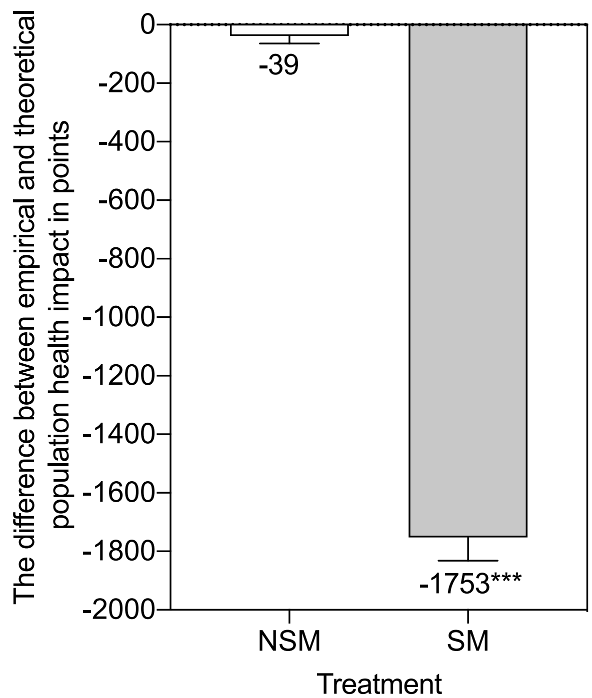
5.4.1 Treatment comparison of population health impact

Based on the pain levels of each round’s final drug consumers, we summarize the round-population-health impact of the incentivized rounds. As shown in Figure 8, the population health impact is significantly higher in NSM than in SM (t-test, $p < 0.01$). This difference is even significantly higher than the theory predicted difference shown in Figure 1(a). The reason lies in the lower-than-predicted prescription thresholds (more than predicted prescriptions) in SM. Such non-cautious prescription behavior led to the lower-than-theory-predicted population health impacts in SM (Figure 9).



Notes: The t-value is 22.72. The p-value is $< .01$. The average round population health impact in NSM is 2909 points and the average health impact in SM is 1031 points.

Figure 8: Histogram of round population health impacts



Notes: Vertical black bars represent standard error of the mean (SEM). ***, $p < 0.01$.

Figure 9: Average difference between the round population health impacts and the theoretical round population health impacts

Therefore, our findings regarding the round population health impact confirm Hypothesis 4. Our fourth result is as follows:

Result 4 - *Prescription bestowed population health impact*
(1) Compared to the population health outcome in the treatment with the secondary market, the round population health impact is significantly better without the secondary market.
(2) The magnitude of health outcome improvement by shutting down the secondary market is significantly higher than the theory prediction.

5.4.2 Disassemble the difference between population health impacts and the theory predicted level

The round population health impact received by the final drug consumers in a round is a mutual outcome of patients' and physicians' decisions in that round. To disaggregate the effect of the two roles in driving the underperformance of population health impacts in SM, we categorize the 104 incentivized rounds of SM treatment as: rounds with threshold = $sick0$; rounds with threshold = $sick1$; rounds with threshold = $sick2$; and rounds with threshold = $sick3$ (shown by Figure 10).

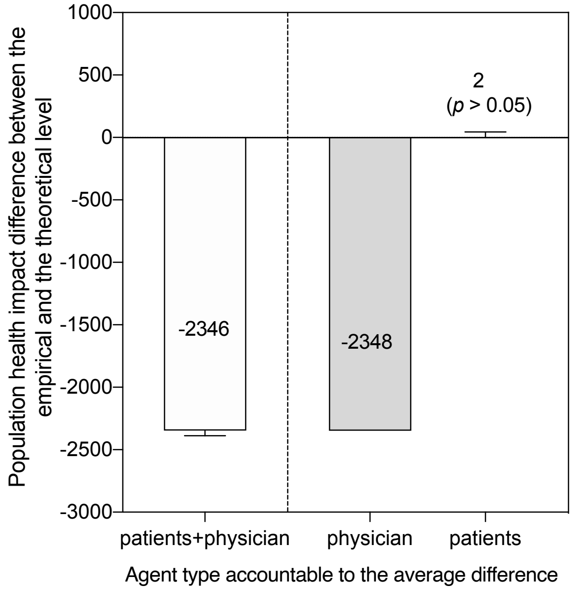
Apparently, in rounds where the physician set the threshold equal to the equilibrium level ($sick3$ for SM), the difference between the round's population health impacts and the theory predicted level is completely (100%) due to the patients' non-optimal behavior (Figure 10 (d)). Likewise, if patients are best responding to each round's threshold, the population health impact gap between the observed round population health impact and the theory predicted level is driven purely (100%) by the non-optimal prescription decision of the physician.

In most rounds in SM (92 out of 104 rounds) shown in Figure 10 (a)(b)(c)), the difference between the observed round population health outcome and the theoretical level is a mutual outcome of the physician and the patients, as the physician and at least some patients were not behaving optimally. The difference between the observed round population health impacts and the theory predicted level can be disaggregated into two parts as shown in (14). The function can be interpreted as: in round t of SM, given the round threshold of κ_{jt} and round decisions of 24 patients $\{\alpha_{it} : \text{i= 1,2,}\ldots 24\}$, the difference between the observed population health impact in round t, $\sum_{i=1}^{N} h(\alpha_{it},\ \kappa_{jt})$ and the theory predicted population health impact $\sum_{i=1}^{N} h(\alpha_{it}^{BR},\ \kappa_{j}^{SM*})$ is disaggregated to the difference due to patients' non-best response to the round threshold ($d1$ in (14)) and the difference due to physicians' deviating from the predicted optimal threshold ($d2$ in (14)).

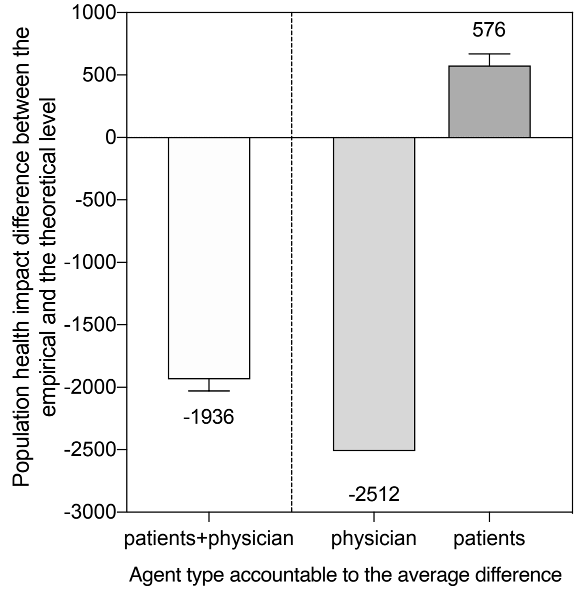
$$\sum_i h(\kappa_{it}^{SM}|(\alpha_{it},\kappa_{jt})) - \sum_i h(\kappa_{it}^{SM}|(\alpha_{it}^{BR},\ \kappa_{jt}^{SM*})) = \tag{14}$$

$$\underbrace{\sum_i h(\kappa_{it}^{SM}|(\alpha_{it},\kappa_{jt})\,) - \sum_i h(\kappa_{it}^{SM}|(\alpha_{it}^{BR},\kappa_{jt}))}_{\text{d1}(\textit{due to patients})} + \underbrace{\sum_i h(\kappa_{it}^{SM}|(\alpha_{it}^{BR},\kappa_{jt})) - \sum_i h(\kappa_{it}^{SM}|(\alpha_{it}^{BR},\ \kappa_{jt}^{SM*}))]}_{\text{d2}(\textit{due to physician})}$$

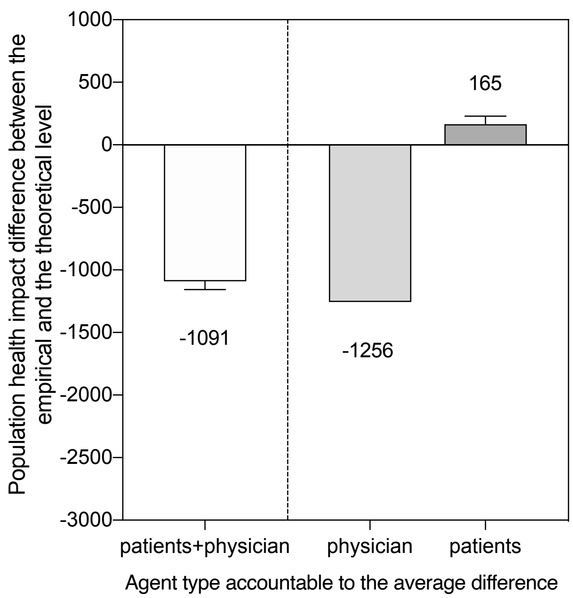
From Figure 10 (a) (b) (c), we can see that the driving force behind the underperformance of population health impacts in SM is physicians' over prescribing behavior (thresholds lower than the predicted threshold $sick3$). Patients' non-best response is not contributing to the lower-than-theory-predicted round health impact. On the contrary, it is canceling off the negative population health impacts caused by the physician's non-optimal threshold decision (Figure 10(b), (c)). The reason behind the positive effect patients' non-optimal behavior contributed to the round population health impacts (Figure 10(b), (c)) is that patients under-transact on average when the threshold is either $sick1$ or $sick2$ (Figure 7).



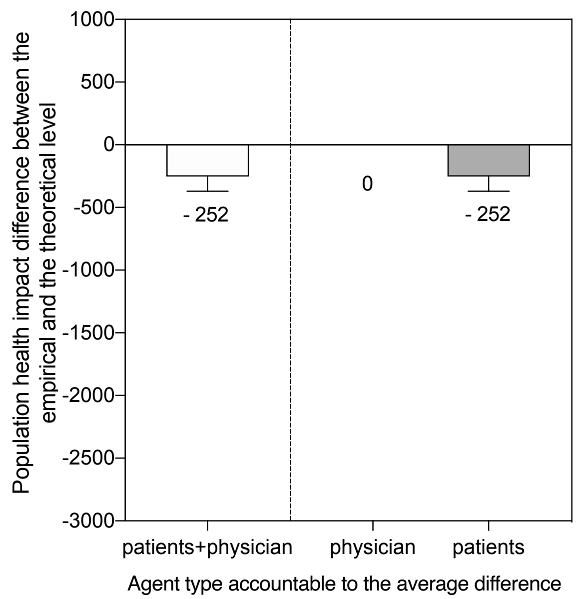
(a) rounds when threshold = sick0 (N = 44)



(b) rounds when threshold = sick1 (N = 26)



(c) rounds when threshold = sick2 (N = 21)



(d) rounds when threshold = sick3 (N = 12)

Notes: Vertical black bars represent standard error of the mean (SEM). * $p < 0.1$, ** $p < 0.05$, ***, $p < 0.01$. In Figure (d), when the equilibrium threshold sick3 was chosen (N = 12 rounds), the patients' non-optimal behavior did not affect the average population health impacts (threshold = sick3) to deviate from the theory predicted level (Mann-Whitney U Test, $p > 0.1$)

Figure 10: Average difference between the population health impacts and the theory predicted level in SM and the player(s) accountable for the difference (when each threshold was chosen)

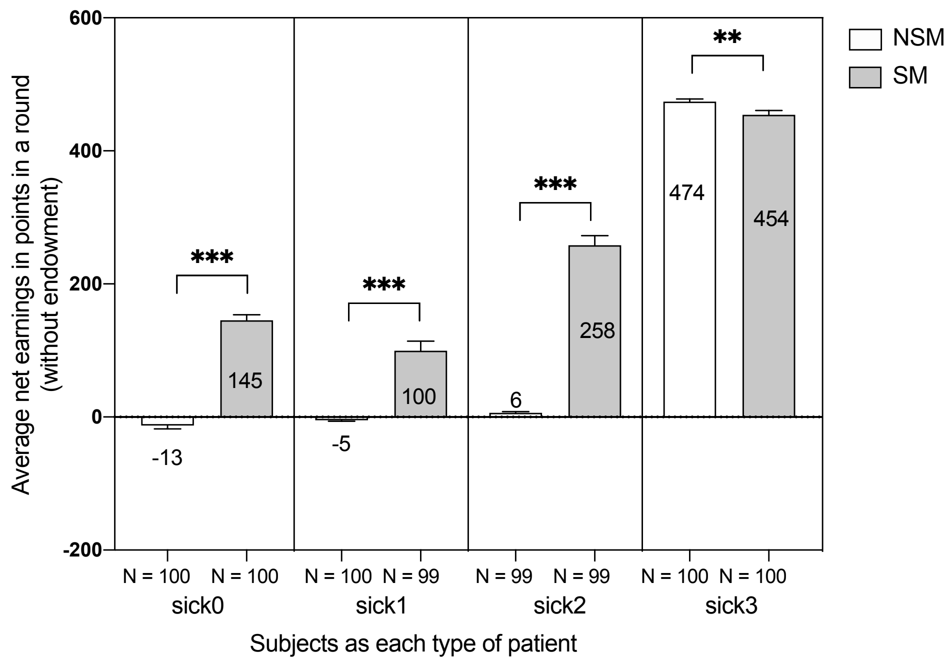
5.5 Social welfare

Do the different pain level patients and the physician all earn more in NSM? To answer this question, we analyze each subject's average earnings as one type of patient and as physician and compare the average earnings as each type of patient and as physician across treatments.

5.5.1 Social welfare of the patients

Based on the net earnings (without endowment) of each subject playing each type of patient, we calculate each subject's average net earnings as each type of patient. We then cluster all the subjects' average earnings as one type of patient and present the average net earnings of each type of patient in Figure 11.

Figure 11 rejects Hypothesis 5 shown in Figure 2 regarding the social welfare improvement of the patients without the secondary market. Instead, we summarize that reselling in the presence of the secondary market, like all the other re-allocation processes, stimulates greater and fairer social welfare among patients, although such social welfare gain harms the population's health outcome.



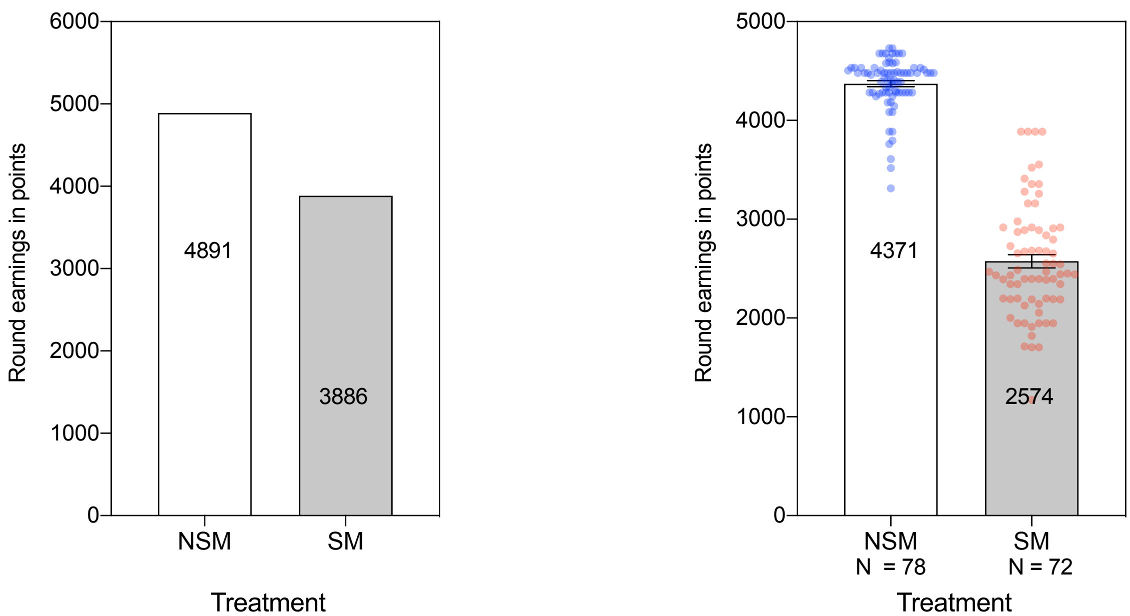
Notes: Vertical black bars represent standard error of the mean (SEM).
* $p < 0.1$, ** $p < 0.05$, ***, $p < 0.01$.

Figure 11: Average net earnings of each type of patients in the two treatments

5.5.2 Social welfare of the physician

Consistent with Hypothesis 5 shown in Figure 12 (a)[32], we find significantly greater welfare of physicians when the secondary market is absent than when it is present.

However, as compared to the theoretical round earnings of the physician in the two cases (Figure 12 (a)), the empirical evidence (Figure 12(b)) displays a greater decline in earnings of physicians when the secondary market is present. As a comparison of Figure 12(b) NSM (white bar) and Figure 12(a) NSM (white bar), 90% of the theoretical earnings are realized as the average earnings of physician subjects in NSM. However, a comparison of SM (grey bars) between Figure 12(b) and Figure 12(a) shows that only 66% of the theoretical earnings are realized as the average earnings of the physicians in SM.



(a) theoretical comparison

(b) empirical comparison

Notes: Vertical black bars in (b) represent standard error of the mean (SEM). Each dot in (b) represents the average earnings of one subject as physician in each treatment. There are 78 blue dots and 72 red dots.

Figure 12: Theoretical and empirical average earnings of subjects as physician in the two treatments

Thus, our finding regarding the social welfare of patients and physician rejects Hypothesis 5, as only the social welfare of physicians is lower in SM than in NSM. Our fifth result is therefore:

[32]Theoretically (shown in Figure 12 (a)), the optimal round earnings of the physician in NSM is achieved when the threshold is $sick1$ and patients behave optimally, α_i^{*NSM}; the optimal round earnings of the physician in SM is achieved when the threshold is $sick3$ and patients behave optimally, α_i^{*SM}.

Result 5 **- *Social welfare***

(1) For the patients with low pain levels or selling incentives, social welfare is economically and statistically significantly higher when the secondary market is present than when it is absent, due to the re-allocation process of the prescriptions.

(2) Physicians' social welfare declines economically and statistically significantly when the secondary market is present than it is absent.

5.6 Risk attitudes and physicians' prescription behavior

So far, we have shown findings regarding the secondary markets' impacts on different dimensions, but the reasons behind some findings, like the over-prescription behavior in SM, have not yet been explained.

Why do physician subjects (who are equally concerned about the population health outcome in the two treatments) set the threshold low in SM, in contrast to what the theory predicts? One possible explanation is the uncertainty faced by physician subjects in SM regarding the prescription-bestowed population health impact. Compared to NSM, the drug diversion process in SM deprives physicians of the ability to control the final allocation of prescriptions. The asymmetric information regarding patients' visit incentives in SM further aggravates such uncertainty.

To test whether uncertainty and risk aversion influence physicians' prescription decisions in SM, below we pool the subjects choosing thresholds $sick0$ and $sick1$[33] in each treatment and compare the risk aversion distribution of subjects choosing the same low thresholds across treatments. We also pool subjects choosing thresholds $sick2$ and $sick3$ in each treatment and compare those high threshold decision-makers' risk aversion distributions across treatments.

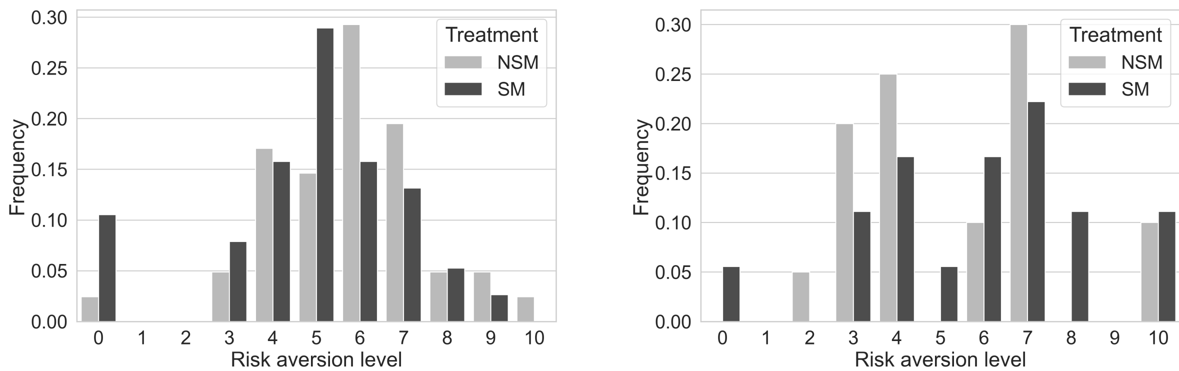
As shown in Figure 13(b), those high threshold makers ($sick2$ and $sick3$) exhibit similar levels of risk aversion across treatments. However, those over-prescribers in SM (sick0 $\cup$ sick1) are less risk-averse than those similar threshold makers in NSM (Figure 13(a), t-test, $p < 0.05$). Moreover, the distribution of risk aversion differs across treatments for those low threshold makers (chi-square test, $p < 0.01$)

This finding reflects the higher uncertainty in SM and provides a potential mechanism to explain the non-precise prediction of physicians' prescription behavior in SM. The reason could be failing to incorporate the extra uncertainty in SM and not incorporating physicians' risk attitudes when making predictions about their behavior. Based on these findings, we reject our Hypothesis 6 and the 6th result is:

Result 6 **- *Risk attitudes and physicians' prescription behavior***

[33]We refer to the subjects who chose thresholds $sick0$ and $sick1$ as over-prescribers.

Risk attitudes influence the over-prescription behavior of the physician when the secondary market is present, which reflects the extra uncertainty when the secondary market is present.
(1) Subjects who set the threshold high (sick2 ∪ sick3) exhibit similar levels of risk aversion across treatments.
(2) Subjects who set threshold low (sick0 ∪ sick1) in SM are less risk-averse than those set threshold low (sick0 ∪ sick1) in NSM.



(a) Low threshold makers (sick0 ∪ sick1) (b) High threshold makers (sick2 ∪ sick3)

Notes: Risk aversion level is the number of non-risky choice(s) subjects made in the risk aversion task. For Figure (a), NSM has N = 41, SM has N =38; for Figure (b), NSM has N =20, SM has N = 18

Figure 13: Histogram of risk aversion levels for physicians setting threshold (a) low and (b) high

6 Discussions

6.1 Physician's prescription behavior

In the presence of a secondary market, why is *sick*0 chosen most frequently by physician subjects. One possible explanation is that the physician wants to keep patients from seeking opportunities on the secondary market. The reason is that physicians might view themselves as being in competition with this alternative market[34]. To ensure the revenues from the prescribed patients, they can relax prescription standards. When competing with legal providers (other physicians or nurse practitioners), previous research suggests physicians prescribe more efficiently (Alexander and Schnell 2019; Brosig-Koch et al. 2017; McMichael

[34]When competing with legal providers (other physicians or nurse practitioners), a physician prescribes more efficiently (Alexander and Schnell 2019; Brosig-Koch et al. 2017; McMichael 2018). However, no previous research has explored whether competing against an illegal supplier will have an opposite effect. According to Dasgupta et al. (2013), the standardized quality of prescription opioids makes the reputation of those sellers less important.

2018). However, no previous research has explored the implications of competing against an illegal supplier. Understanding physician prescription motives in the presence of competition from the secondary market is an important area for future research. Besides, the findings of physicians' risk attitudes influencing their prescription behavior, especially when the secondary market is present have important implications for over-prescription-related policies in the natural environment.

Another possible explanation for over prescription in our SM treatment is that uncertainty caused by secondary markets creates complexity for physicians and may reduce their ability to make good prescription decisions. Our findings resonate with a growing literature suggesting that improved physician decision-making can emerge when physicians are provided more information about the specific circumstances of their patients, particularly those struggling with addictions (Abouk and Powell 2021; Buchmueller and Carey 2018; Feldman et al. 2011)[35].

6.2 Opioid Policy

Although completely shutting down the secondary market would be extremely difficult, practices aimed at restricting activities on the secondary market could be considered. One example would be increasing punishment of illegal activities related to the sale of opioids. As shown by Chang (2020) in the context of Florida, higher punishment for illegal possession, manufacture, or trafficking of prescription opioids results in significantly lower numbers of opioid overdose deaths.

Other policies that could be considered include finding ways to reduce demand and supply on the secondary market. One way to reduce the demand could be to reduce prescriptions, potentially leading to a reduction in the population of addicted drug abusers. Another way could be through targeting and giving assistance (Medicine-Assistance-Treatment) to the heavily addicted drug abusers, so that they do not enter the unregulated secondary market[36]. This could help reduce the long-term illegal supply of the opioids. Additional examples include gentler policies like PDMP (prescription drug monitoring program) involving stricter screening, as well as intermediate approaches like quotas, which could reduce supply and

[35]A previous study by Buchmueller and Carey (2018) confirms the effectiveness of PDMP in lowering opioid abuse and diversions only when the database is required to be accessed. Another study Feldman et al. (2011) found that less than 59% of physicians who were aware of PDMP had ever used it. A recent study by Abouk and Powell (2021) found that mandated e-prescribing, which forces physician to access the data in PDMP, could reduce the likelihood of prescription errors and forgery and reduce opioid mortality by 22%.

[36]The substitution effect towards heroin and high potency illicit opioids when PDMP is popularized is always a concern as the cost of being caught diverting prescription drugs can increase the price of prescription opioids and incentivize dealers of illicit opioids to manufacture more potent drugs (Minhee and Calandrillo 2019).

consequently dampen secondary market activities.

7 Conclusion

While prescription opioids provide important medical benefits, they can also be consumed by abusers via diversion channels on the secondary market. We collected data from an experiment designed to test the effect of secondary markets on physician and patient behavior. Our experiment reveals that eliminating the secondary market for opioids changes both the behavior of physicians and patients, and that such changes improve health outcomes[37]. The presence of the secondary market, on the contrary, leads to a more severe over prescription problem and creates uncertainty over the public health consequences of physicians' prescription decisions. Facing this uncertainty, physicians' prescription behavior can be impacted by their own risk attitudes. This creates an additional layer of complexity in determining the theoretical effects of the secondary markets.

Our results suggest that secondary markets may be even more harmful to public health than theory would predict. Our findings emphasize the importance of enforcing existing laws prohibiting the trade of opioids in secondary markets and highlight the importance of creating policies that constrain both the supply of and demand for opioids on secondary markets. Among the current policies that constrain the activities on the secondary market, PDPM is one that has gained a widespread attention due to its practicality and moderate cost[38], especially as compared to the cost of lost lives (estimated to be in the billions of dollars)[39]. In general, policies that reduce drug diversions into the secondary market could be combined with lowering the incentive to sell via increased punishment[40], while also reducing the availability and accessibility[41] of prescription opioids through the use of physician quotas.

The reason that we think future research should focus on quotas is because such poli-

[37]In the short run, our estimation for the population health impact could be overstated, as the shortage of prescription opioids when the secondary market is removed could lead to cross product substitution, and we should expect a negative impact in health due to high facilities from the substituted illicit opioids. However, in the long run, we do think the population health improvement should be greater than our estimated effect due to the reduced demand and supply on the opioids market.

[38]PDMP costs vary widely, with startup costs that can range as high as $450,000 to over $1.5 million and annual operating costs ranging from $125,000 to nearly $1.0 million (Sacco et al. 2018). Such costs are much lower than the otherwise increased cost of life losses (amounted to billions of dollars) due to over prescriptions and drug diversions.

[39]Florida's Senate estimates that by relaxing the criminal standard on the secondary market of opioids saved approximately $2.2 million in prison operating costs, however, it comes with the cost of an additional 491 opioid deaths which amounted to approximately $2.2 billion (Chang 2020).

[40]Doleac and Mukherjee (2019) discuss behavior changes of drug users in response to incentives and shows that they responded very well even if being addicted drug users.

[41]Other policies that increases the accessibility and availability of the life-saving medication and drug equipment (e.g. needles), come with the cost of public health losses (Packham 2019).

cies could help reduce the supply and activities on the secondary market. Likewise, there are unsolved questions regarding whether quota policies can improve population health outcomes by better allocating prescription drugs (not at the expense of those in genuine pain). Although the Drug Enforcement Administration (DEA) has embarked on a campaign of annually reducing the Aggregate Production Quota (APQ) of opioids each year since 2017, little empirical evidence has been provided towards understanding the basis for setting quotas. Investigating how to create an effective quota policy would be an important next step towards improving public health outcomes.

A Appendix: Experimental instructions (Use *SM* as examples)

Thank you for agreeing to participate in today's experiment. You are about to participate in a decision-making experiment and at the end of the session you will be paid in cash based on your performance. By showing up, you have already earned \$5. If you finish the experiment, at the end of this session, you will earn an additional \$5 participation fee.

Today's experiment consists of 3 parts. At the beginning of each part, you will receive new instructions. You will spend most time on first part. Your decisions in one part have no influence on the proceedings or earnings of the other parts.

Your decisions and those of other participants will determine your earnings. Your earnings will be paid to you privately at the end of today's session. Your earnings in Part 1 will be denoted in points. At the end of the experiment, each point that you earned will be converted into 1 US cents (1 point = 0.01 US dollar).

Part 1: Decisions and Payoffs
This part consists of 30 rounds. In each round of this experiment, only 1 participant will be randomly chosen as a physician, the rest 24 participants are patients. At the beginning of each round, the role of each participant could be updated. There will be 4 practice rounds, the final payment is a random draw from the 5th to the 30th rounds. Thus, your role, decision and other participants' decisions in that round determine your final payment.

<u>Initial endowment:</u>
Each **patient** player is endowed with 653 points at the beginning of each round. The **physician** player of each round has no endowment.

<u>Role Introduction:</u>
• All the patients in this experiment are sick. But sicknesses can differ in their severity level. Each patient's sickness level determines how much "health impact" she/he could get from consuming a drug. The more severe the sickness, the more benefit the drug can bring to the patient. Because the drug can have negative side-effects, patients who are not very sick could be harmed, overall, by taking the drug. The drug can also bring different patient different levels of enjoyment. The enjoyment level has no relationship to a patient's sickness level. Thus, it is possible that a patient who is not very sick could enjoy taking the drug a

lot; whereas a patient who is very heavily sick might only receive little enjoyment from the drug.

For sickness levels, we differentiate the patients by 4 levels, from lowest to highest: sick, sick*, sick**, sick***. The different levels of enjoyment are, from lowest to highest: enjoy, enjoy*, enjoy**, enjoy*** (4 levels). As sickness levels are unrelated with enjoyment levels, there are 16 different combinations, and each patient only knows her/his combination but not the combination of others. Each sickness level is associated with a health impact number, and each enjoyment level is associated with a specific number. The sum of the "health impact" and the "enjoyment level" is the drug's value to the patients. The greater those two numbers are, the more the drug can contribute to the patient's payoff in that round.

• The physician in the market can observe all patients' sickness levels, but not the enjoyment levels. The physician's payoff is based on the health impact of the patients who eventually consumed the drug.

Table 1: possible **sickness levels** and **enjoyment levels** and their associated numbers

Sickness levels (x-axis number on the figure of *welcome page*)	Sick (x = 0.94)	Sick* (x = 1.4)	Sick** (x = 1.7)	Sick*** (x = 2.5)
Health Impact (Value in points)	-314	-45	86	348

Enjoyment levels (Value in points)	Enjoy	Enjoy*	Enjoy**	Enjoy***
	50	165	250	1000

Environment Introduction:

Please note, there is a primary market, where the physician can prescribe a drug to the patients who visit. Also, there is a secondary market, where the patients can sell (buy) the drug which they previously received (not received) from a physician. The physician has no control over secondary market activity. However, the physician's payoff in a round is determined by the secondary market's transaction results: total health impacts of those patients who eventually take the prescription in that round.

Your decision (as patient player) & Payoffs

(Please look at the figure at the end of this instruction for possible outcomes info):
As a patient, your decision consists of 2 components (I and II):

I. **Decision in the primary market**: Visit the physician or not
A. Visit (653 points endowment - 103 Points visit fee = 550 Points)
(You need to pay 103 points visit fee regardless whether the physician prescribes to you)
B. Not visit (653 points endowment)

II. **Decision in the secondary market (associated payoff)**
Your available choices depend on the outcome at the end of the primary market phase.

- Possible Outcome 1: the patient visited and then got the drug from the primary market

(653 points - 103 points - 15 points drug fee)
A. **Sell** (+550 points)
B. **Consume** (+Health impact +Enjoy)

- Possible Outcome 2 & 3: the patient did not get the drug from the primary market

$$\begin{cases} Route\ of\ outcome\ 2: the\ patient\ visited\ and\ did\ NOT\ get\ the\ drug\ from\ the\ primary\ market \\ Route\ of\ outcome\ 3: the\ patient\ did\ not\ visit \end{cases}$$

A. **Buy** (-550 points)
  – if visited (653 – 103 – 550 + Health impact + Enjoyment level)
  – if not visited (653 – 550 + Health impact + Enjoyment level)
B. **Not get the drug**
  – if visited (653 -103 = 550 Points)
  – if not visited (653 Points)

**Note*: If the number of the buyers and sellers on the secondary market is not equal then not all buyers and sellers will be able to transact successfully. For example, if there are 5 sellers and 3 buyers then all 3 buyers can purchase the drug while 2 sellers would not be able to sell, and similarly if there are more buyers than sellers. This example also indicates that "buy" or "sell" decision will not necessarily lead to a successful transaction which involves 550 points (revenue for 'sell' patients AND expenditure for 'buy' patients are thus just pending if you hit "sell" or "buy" button, the transaction will not necessarily be executed).

Decision of physician:
As the patients decide whether to visit, the physician sets a threshold sick level for a prescription. The patient needs to be at least as sick as the threshold level to get the prescription from the physician. As the physician can see the profile of every patient (sickness level and

the "health impact" bring by the drug), the physician is actually deciding who to prescribe in the primary market by setting this threshold sick level. The physician knows nothing about each patient's enjoyment level throughout the experiment.

Physician Payoff

Once all the patients have made their visiting decisions and the physician has made the threshold sickness level decision, the patients know whether or not she/he gets the prescription at the end of the "primary market" phase. Then all the patients enter the "secondary market" to make transactions. Once the transactions have completed, each patient knows their own transaction result. And the physician knows the patients to whom he/she prescribed the drug, as well all the people who ultimately consume the drug based on secondary market transactions.

Unlike the patient who cares about self-received-health-impact AND enjoyment level, the physician cares about the health impact on all patients who consume the drug.

◊ The payoff of the physician is the sum of the 2 parts below:

- *Visiting fee*:

  $\boxed{Number\ of\ visitors\ who\ reached\ the\ threshold\ sickness\ level \times (103\ points)}$

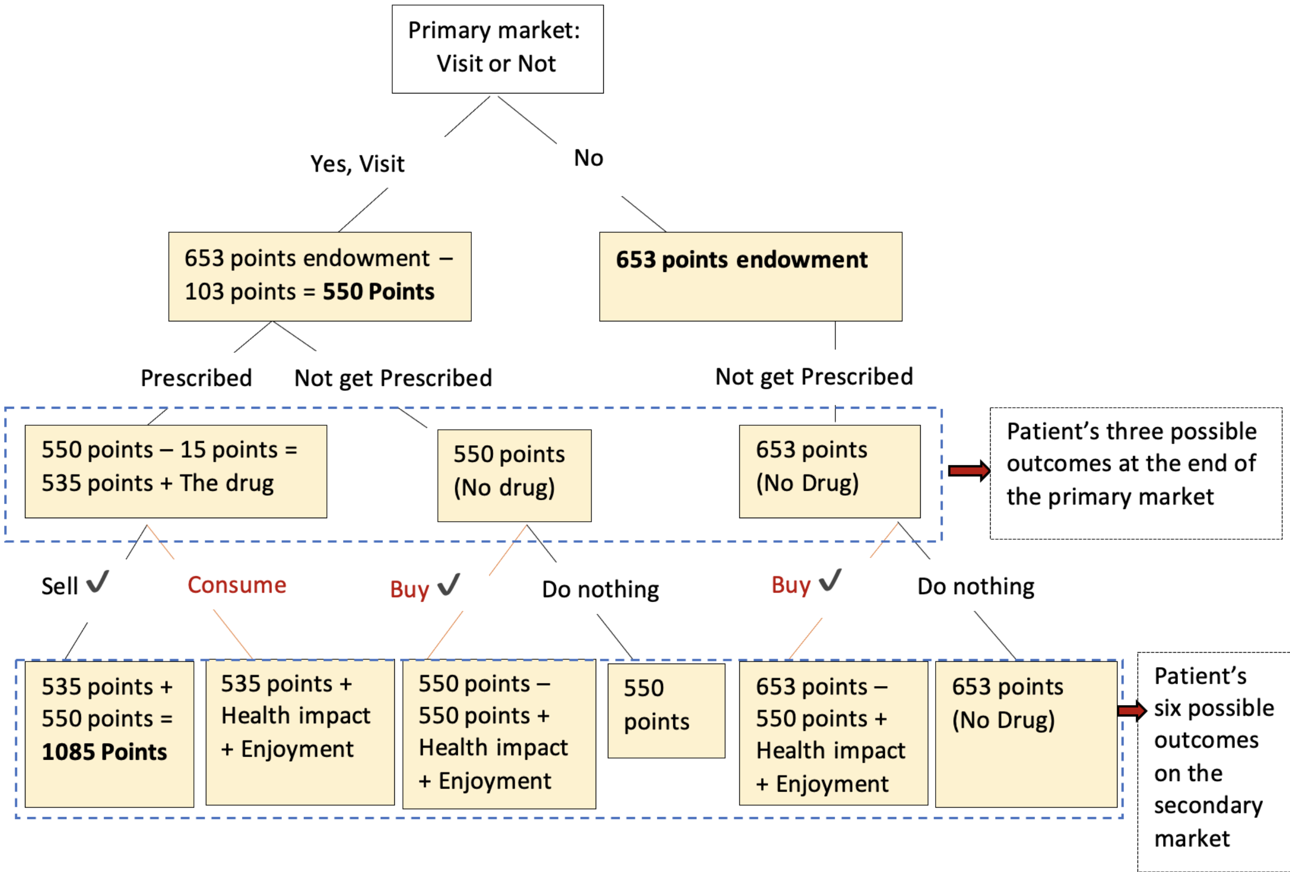
- *Health impact Part*:

  $\boxed{1.1 \times Sum\ of\ the\ health\ impact\ of\ \textbf{those patients who consumed the drug}}$

  $(successful\ secondary\ market\ buyers\ AND\ prescribed\ patients\ who\ consume)$

For detailed information about physician's payoffs, how the payoffs would change when making different threshold sickness level decisions AND how the payoffs would be impacted by different sickness level patients' decisions, please look at the dynamic table on your computer before choosing a formal threshold sickness level to submit.

This is the end of the instructions. You will be given a short quiz to ensure that you understand the instructions. Once you complete the quiz successfully, you'll proceed to the experiment.

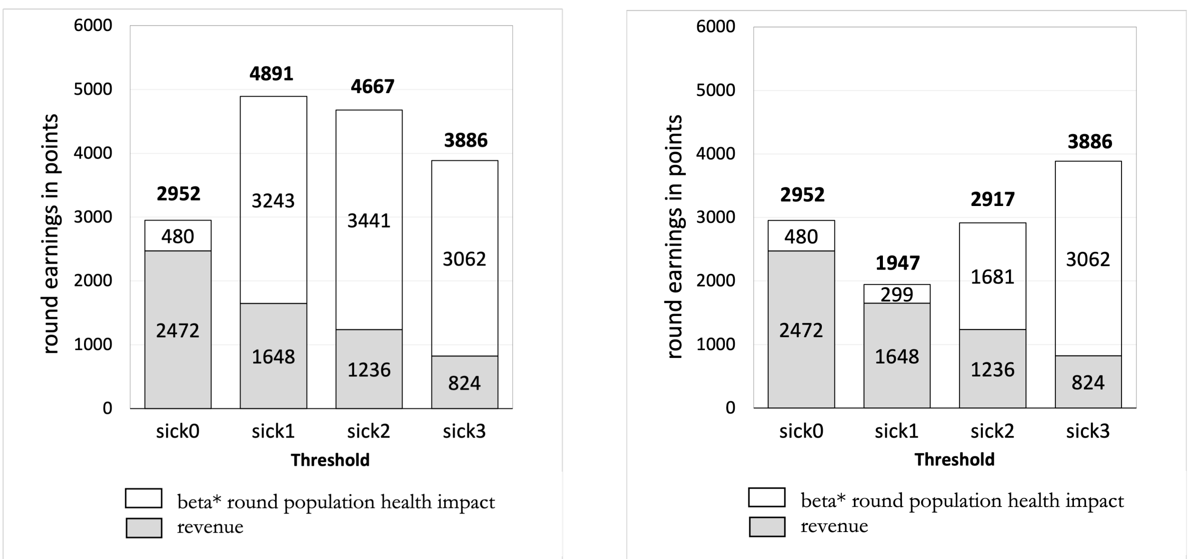


Among the 6 final results (last row of the figure above). Result 2, 3, 5 (last step route marked red) are the 3 cases that you can get the drug after going through secondary market, the routes are:

- *Result 2: 'Yes, visit'→'Get Prescribed' → 'consume'*
- *Result 3: 'Yes, visit'→ 'Not Get the Prescription'→ 'Buy successfully'*
- *Result 5: 'No'→ 'Not Get the Prescription'→ 'Buy successfully'*

B Appendix: Supplementary analysis

The figure below shows the theoretical payoff of the physician, $u_j(\kappa_j|\alpha_i^*)$, where the payoff is the function of physician's threshold decision, κ_j, given that the patients choose the optimal decision, α_i^* under each threshold. Under the complete information of the patients, in NSM, $\alpha_i^{*NSM}(\kappa_i \geq \kappa_j) = visit\ (consume)$ for all the patients; $\alpha_i^{*NSM}(\kappa_i < \kappa_j)$ $= not\ visit\ (not\ consume)$ for all the patients; in SM case, $\alpha_{sick0}^{*SM}(\kappa_i \geq \kappa_j) = \alpha_{sick3}^{*SM}(\kappa_i \geq \kappa_j) = visit \times consume$, $\alpha_{sick0}^{*SM}(\kappa_i < \kappa_j) = \alpha_{sick3}^{*SM}(\kappa_i < \kappa_j) = not\ visit \times consume\ by\ buy$; $\alpha_{sick1}^{*SM}(\kappa_i \geq \kappa_j) = \alpha_{sick2}^{*SM}(\kappa_i \geq \kappa_j) = visit \times sell$, $\alpha_{sick1}^{*SM}(\kappa_i < \kappa_j) = \alpha_{sick2}^{*SM}(\kappa_i < \kappa_j) = not\ visit$ $\times\ do\ nothing$. Figure B1 demonstrates how larger incentive the physician have to choose $sick1$ as the threshold in NSM (comparing the payoffs of choosing other thresholds) and how larger incentive the physician have to choose $sick3$ as the threshold in SM (comparing the payoffs of choosing other thresholds).



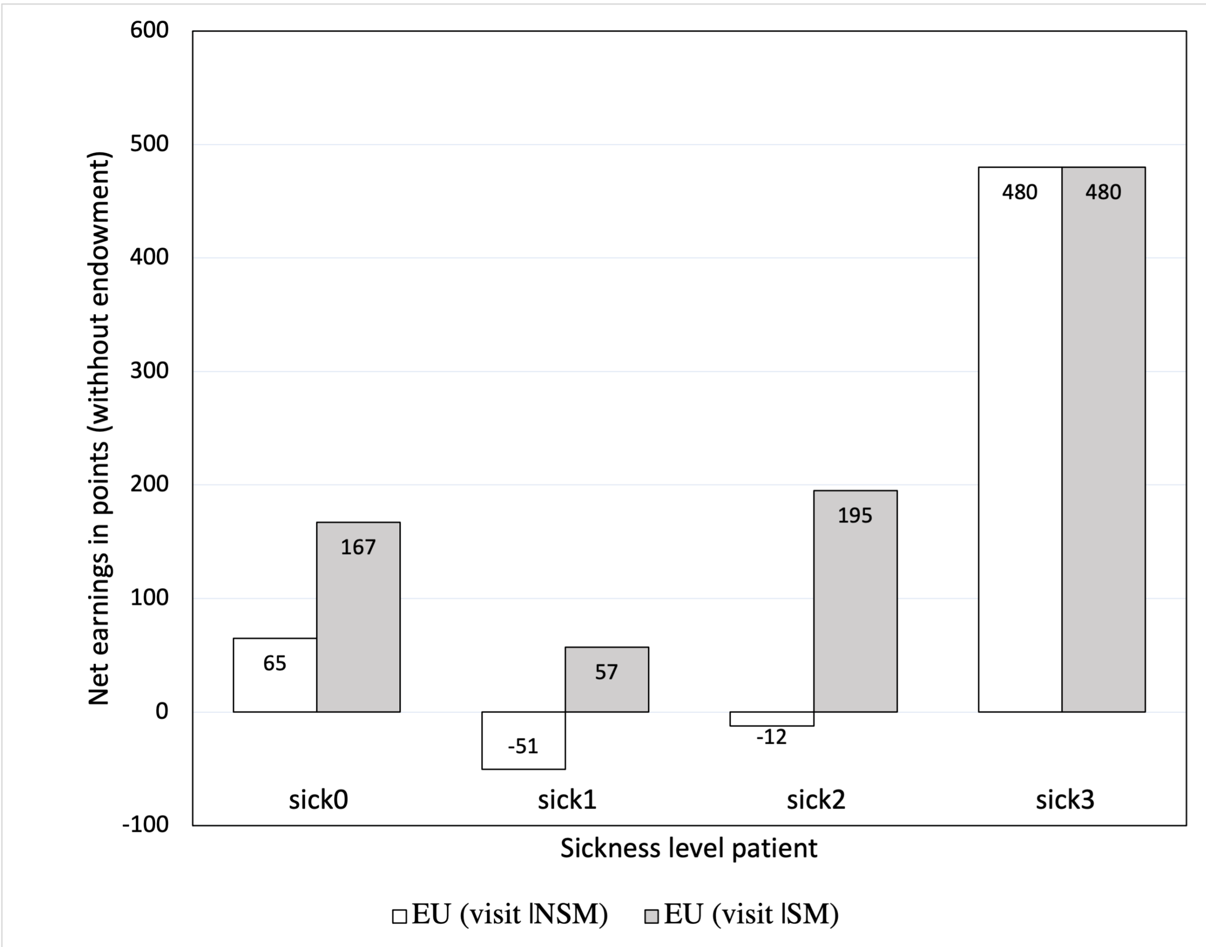
(a) NSM

(b) SM

Notes: 100 points = \$1. For example, when the threshold is $sick1$, in NSM, $u_j(\kappa_j|\alpha_i^*)$ is calculated given $\kappa_j^{NSM} = sick1$, $\alpha_{sick0}^{*NSM} = not\ visit\ (not\ consume)$; $\alpha_{sick1}^{*NSM} = \alpha_{sick2}^{*NSM} = \alpha_{sick3}^{*NSM} = visit\ (consume)$

Figure B1: theoretical payoff of the physician when choosing each threshold in the two treatments under complete information settings (given that the patients best responding to each threshold)

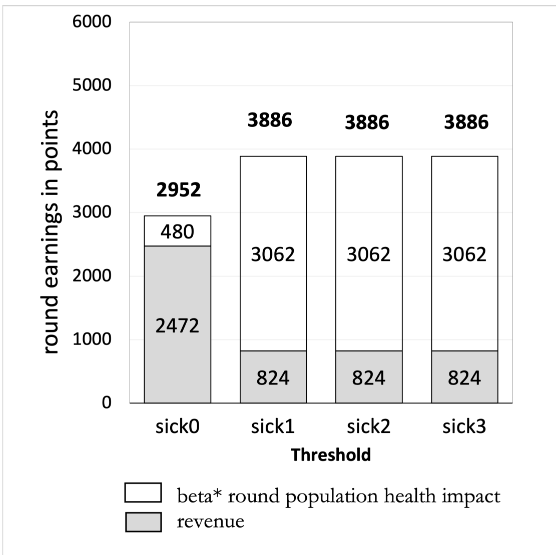
Figure B2 below shows the expected net earnings (without endowment) of each sickness level patient choosing α_i= *visit* on the legal market when holding incomplete information regarding the threshold. The grey bars below (which are all positive) demonstrates that $\alpha_i^{BR}(SM)$=*visit* for $i = 1, 2, 3...24$. The white bars below (which falls negative for patients of sick1 and sick2) demonstrates that $\alpha_{sick1}^{BR}(NSM) = \alpha_{sick2}^{BR}(NSM) =$ *not visit*; $\alpha_{sick0}^{BR}(NSM) = \alpha_{sick3}^{BR}(NSM) = visit \times \{consume,\ not\ consume\}$. Whether patients of sick0 and sick3 can consume after *visit* depends on whether his pain level reaches the threshold.



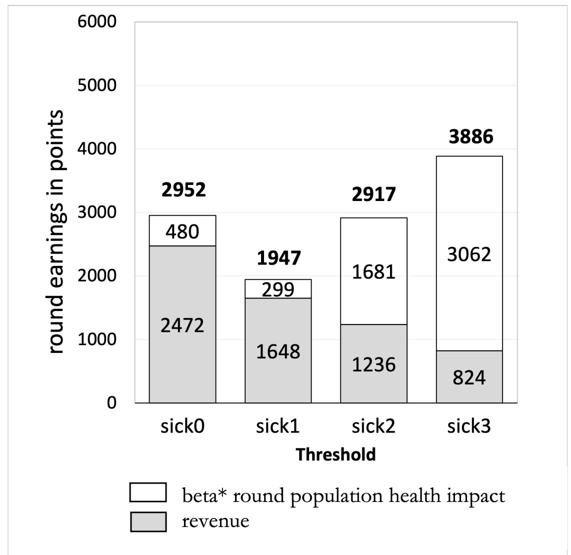
Notes: For example, a sick0 patient's expected net earnings in NSM by choosing *visit* is: $EU(\alpha_{sick0}^{NSM} = visit) = Prob(\kappa_j = sick0) \cdot U(\alpha_{sick0}^{NSM} = visit \times consume)$ + (1-$Prob(\kappa_j = sick0)$)$\cdot$ $U(\alpha_{sick0}^{NSM} = visit\ (not\ prescribed))$ = 1/4 $\cdot$ $U(\alpha_{sick0}^{NSM} = visit \times consume)$ + 3/4 $\cdot$ (-103) = 65; a sick0 patient's expected net earnings by choosing *visit* in SM is: $EU(\alpha_{sick0}^{SM} = visit) = Prob(\kappa_j = sick0) \cdot U(\alpha_{sick0}^{SM} = visit \times consume)$ + (1-$Prob(\kappa_j = sick0)$)$\cdot$ $U(\alpha_{sick0}^{SM} = visit \times consume\ by\ buy)$ = 167.

Figure B2: expected net earnings of each sickness level patients choosing *visit* in each case (under incomplete information settings)

Figure B3 below shows the expected payoff of the physician $u_j(\kappa_j|\alpha^{BR})$, where the payoff is the function of physician's threshold decision, κ_j, given that the patients choose the best response decision, α_i^{BR} **not** knowing about the threshold. The figure demonstrates that in NSM, given $\alpha_{sick0}^{BR}(NSM) = \alpha_{sick3}^{BR}(NSM) = visit$; $\alpha_{sick1}^{BR}(NSM) = \alpha_{sick2}^{BR}(NSM) = not\ visit$, threshold of $sick1$, $sick2$ and $sick3$ can all achieve the maximal payoffs for the physician (Shown in figure B3(a)). Given $\alpha_i^{BR}(SM)$=$visit$ for $i = 1, 2, 3...24$, the threshold of $sick3$ is still the equilibrium threshold under the incomplete information settings of the patients (Shown in figure B3(b)).



(a) NSM

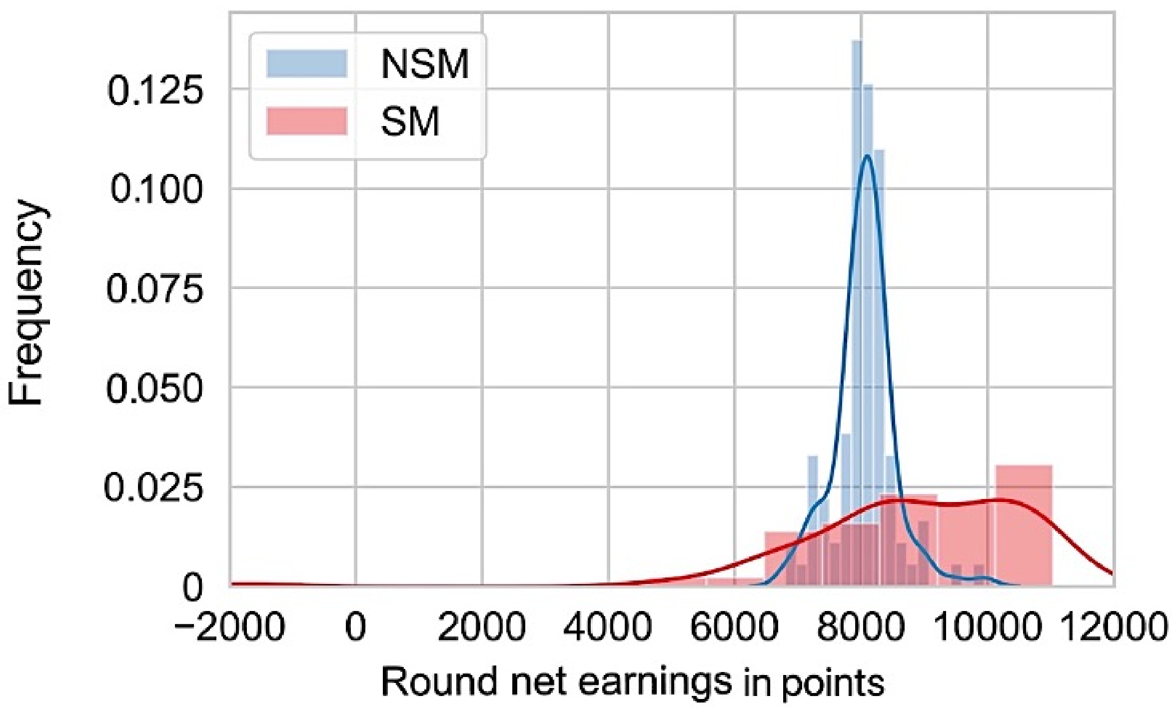


(b) SM

Notes: 100 points = \$1

Figure B3: theoretical payoff of the physician when choosing each threshold in the two cases given the best response of the patients under incomplete information settings

Clustering each treatment's 104 incentivized rounds' round-net-earnings of 25 subjects (in points without adding endowment of each patient subject), Figure B4 below shows the distribution of the round net earnings of each treatment. Contrary to Hypothesis 4, the round earnings achieved (Figure B4) are significantly higher in SM than in NSM (t-value = -4.45, p <.01).



Notes: frequency displayed (y-axis) = real frequency*10ˆ2. Round net earnings in points (x-axis) do not include the endowment of each patient. The treatment effect regarding the round net earnings is significantly ($p < .01$), N =104. The average round earnings in NSM is 8049 (significantly lower than the theory predicted level 8811, $p < .01$); the average round earnings in SM is 8862 (significantly higher than the theory predicted level 7726, $p < .01$).

Figure B4: Histogram of round net earnings in points

Table B1: risk aversion level distribution for physicians choosing each threshold in NSM (N = 61)

Threshold / Risk aversion level	Sick0	Sick1	Sick2	Sick3
low	0	3	3	2
middle	5	20	6	1
high	1	12	7	1

Notes: Risk aversion is the number of non-risky choice(s) subjects made in the risk aversion task, with number ranging from 0-3 categorized as low risk aversion type; number ranging from 4-6 categorized as middle risk aversion type; number ranging from 7-10 as high-risk aversion type

Table B2: risk aversion level distribution for physicians choosing each threshold in SM (N = 56)

Threshold / Risk aversion level	Sick0	Sick1	Sick2	Sick3
low	3	4	2	1
middle	12	11	5	2
high	6	2	6	2

Notes: Risk aversion is the number of non-risky choice(s) subjects made in the risk aversion task, with number ranging from 0-3 categorized as low risk aversion type; number ranging from 4-6 categorized as middle risk aversion type; number ranging from 7-10 as high-risk aversion type

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