Prices and Policies in Opioid Markets

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Opioid mortality increases have been linked to both lax and restrictive opioid prescription regulations. Modeling choice between prescription and illicitly manufactured opioid sources helps reconcile the apparently contradictory empirical findings. It also identifies groups responding opposite of the average and applies previous studies to new supply conditions. Organized around the two supply channels, a policy database is assembled that reveals distinct pricing phases during 1999–2021. Consistent with the model, during the later phases the relationship between the opioid fatality rate (measured from death certificates) and its composition changes sign, minors' fatality rates trend opposite of adults', and the black-white gap changes sign.

I. Introduction

In both 2015 and 2016, US life expectancy fell from the previous year. This marked the first single-year drop since 1993 and the first instance in more

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than 50 years with two consecutive annual declines. The sharp reversal in the national trend toward longer lives is widely understood to be connected to the opioid epidemic, whose annual US costs are approaching a trillion dollars. A similar reversal may be soon observed in other countries and regions where fatalities involving opioids have already increased by several multiples in a decade or so.[1] The fatalities likely indicate millions more consumers who still struggle with opioid addictions.

This paper presents an economic model of choosing between prescription (Rx) and illicitly manufactured (Im) sources of opioids for nonmedical use.[2] Although simple, it unifies and helps explain a range of policy effects that have been documented in the literature, as well as new empirical results. The model also shows what previous findings on, say, Rx regulation, may reveal about other technological and regulatory changes in opioid markets that would appear unrelated to prescriptions. The predictions of an economic model are especially valuable for opioid markets, where data can be sparse and policy analysis might rationally put more weight on potentially relevant lessons from other contexts.

Medical experts advising or serving as policymakers typically ignore the interplay between Rx and Im delivery channels. As recently as 2022, the Stanford-*Lancet* Commission on the North American Opioid Crisis recommended changes in law enforcement and Rx regulations without acknowledging that their proposals might increase both demand and supply in illicit markets (Humphreys et al. 2022). The US Food and Drug Administration, which oversees the marketing of prescription products, elects not to consider costs that accrue in heroin or fentanyl markets, because those markets are outside their jurisdiction (Mulligan 2020).

The economic model suggests that each supply channel is better understood in the context of the other. Accessing potentially cheaper illegal opioids involves fixed costs in the form of establishing supply contacts, gaining knowledge of potency and administration, and overcoming stigma and fear. That is, nonmedical opioid use involves a kind of human capital investment, albeit one oriented toward consumption rather than work. Opioid source and the quantity consumed are jointly determined.

As a result of fixed costs, consumers potentially face a nonconvex budget set, with a high marginal price at low levels of opioid consumption and a low price at high levels. A change in either Rx or Im price has two consequences

[1] Opioid death rates in Sweden, Northern Ireland, and British Columbia increased by a factor of about six, surpassing by 2018 or 2019 the rates that the United States had as recently as 2013 (Pardo et al. 2019, chap. 4; NISRA 2020). Period life expectancy is FRED (Federal Reserve Economic Data) series SPDYNLE00INUSA. Opioid costs are from Murphy (2020); they include the value of lost lives and other costs but no offset for "consumer surplus."

[2] Opioids include Rx painkillers such as oxycodone (an active ingredient in OxyContin and Percocet) and hydrocodone (an active ingredient in Vicodin) as well as morphine and Im drugs such as heroin, illicit fentanyl, and fentanyl analogs.

for market aggregates: a jump from one part of the budget set to another among consumers indifferent between opioid sources and the ordinary movement along individual-level demand curves among the others. The former is a large change among a few consumers, while the latter is a relatively small change among many. The two can be in opposite directions, and either can dominate in the aggregate. A contribution of this paper is a sufficient-statistics expression for comparing the two magnitudes, in both the short and long runs, and for identifying groups for whom one or the other effect is especially likely.

A previous econometric literature has already warned that policies aimed at reducing Rx opioid consumption can lead to increased mortality in the short run due to widespread substitution to Im opioids. Many of the papers provide convincing evidence that this may be the case in the United States in 2011 and subsequent years, often citing “existence” or “availability” of heroin as a critical factor driving this result.[3] At the same time, increased mortality in an earlier era, when heroin was also available, has been attributed to just the opposite: policies and business practices that increased Rx consumption (Pacula and Powell 2018; Alpert et al. 2022). The economic model clarifies that switching sources is not merely regulatory avoidance but also changes the quantity consumed among those who switch. It therefore points to the price gap between Rx and Im opioids as the critical determinant of both the sign and the magnitude of the effects of prescription policies.[4] Although measuring illicit prices is subject to significant measurement error, it is generally understood that Rx opioids were once “poor man’s heroin” but more recently “heroin is cheaper and easier to get than prescription opioids”(NDIC 2001 and NIDA 2021, respectively).

More important, the model adds valuable predictions. It shows which groups may experience reduced mortality from Rx regulation even if the general population does not. It shows how much the current Im market must change to bring opioid markets back to a more conventional era when opioid mortality varies inversely with Rx-opioid prices. It helps explain why some studies link Im consumption to Rx access in the past (Alpert et al. 2022), while others cite a lack of Rx access (Alpert, Powell, and Pacula 2018). The model even tightly links the consequences of Rx price changes such as those associated with regulation; effects of Im price changes resulting from technological progress in Im opioid manufacturing or the treatment of health conditions resulting from intravenous drug use or from changes in law enforcement; and effects of price changes common to the two sources, including opioid overdose treatments and changes

[3] See Meinhoffer (2018), Powell, Alpert, and Pacula (2019), Powell and Pacula (2021), and the studies cited in sec. IV. Maclean et al. (2020) is a survey of opioid economics generally.

[4] Evans, Lieber, and Power (2019) and others discuss an independent influence of heroin prices on drug consumption and mortality but not on the sign or magnitude of the effect of Rx regulation. Analysis of the gap between heroin and Rx prices is not attempted.

in labor market opportunity costs of opioid consumption. When only one set of consequences is part of the available evidence base, the link strengthens policymaking that would otherwise be limited to postmortem analysis: waiting for mortality to accumulate before reaching conclusions about the other sets (Ruhm 2019b). A conceptual framework that sheds light on the generalizability of the historical evidence base helps save lives, especially in a market where even the direction of policy effects varies over time. To use a metaphor, confusing the policy gas and brake pedals is a tragic mistake that a conceptual framework helps avoid.

With the exception of Schnell (2018), the economics literature on Rx regulation had no formal analysis of opioid consumption incentives.[5] "Elasticities" are sometimes part of the discussion, but no indication is given as to which demand or supply elasticities are needed to explain why opioid markets reached the point that opioid mortality would increase with Rx prices. An economic model helps reconcile apparently disparate findings and draw lessons from previous studies, even for policy environments with new supply conditions.

Section II's model offers six empirical predictions in the form of formal propositions. The death certificate and opioid price data are described in section III, including a new federal policy database revealing distinct pricing phases during 1999–2021. The four propositions that are testable with those data are the subject of section IV. One test is whether the cross-area relationship between opioid fatalities and its composition changed sign when Im prices fell and Rx regulations tightened. A second test is whether, coincident with the OxyContin reformulation and new Rx regulations, opioid deaths fell for children and youth, whose opioid consumption appeared to be especially Rx intensive. Both predictions are confirmed. The second empirical finding at least directionally supports the gateway hypothesis that Rx regulation reduces opioid initiation, potentially reducing opioid demand and net mortality in the long run.

By 2008, African Americans stood out as having lower opioid mortality rates relative to whites. If much of the differential was due to unequal Rx access, then the third prediction is that black mortality rates would eventually surpass white rates once Im prices fell enough. A fourth prediction assesses the pace of the race reversal. Section IV confirms that black mortality rates did surpass white rates, holding constant gender, age group, and

[5] Schnell (2018) builds an equilibrium model of switching between primary Rx and (unlawful) secondary Rx markets that shows conditions under which the two would be close substitutes. Greenwood, Guner, and Kopecky (2022) is a new paper modeling transitions between medical and nonmedical prescription use. CEA (2019, fig. 10) is a demand-residual analysis quantifying the degree to which declining Rx prices explain rising Rx mortality. The formal analysis in the rest of the literature is so far confined to equations showing econometric specifications (data construction, the use of fixed effects, etc). There are several formal models of drug demand generally.

geographic area. Moreover, as predicted, the race reversal occurred first among older people and near the predicted pace. Section V discusses possible model extensions, followed by the concluding section VI.

II. Opioid Policies and the Consumer Budget Set

Model agents have preferences over two composite commodities: opioids Q and "all other goods" z. The preferences are represented by the function $u(Q, z; \theta)$, where u is strictly quasi-concave in Q and z. The scalar θ is a shifter of the marginal rate of substitution used for derivations as well as a representation of the influence of past opioid consumption, as in models of habit, addiction, and drug tolerance (Pollak 1970; Becker and Murphy 1988). The rate of exchange between the composites is the full price of opioids, including consumer time, effort, stigma, and the expectation (if any) of criminal penalties as well as out-of-pocket costs. Although the nonlinearity of the budget constraint is essential, the indirect utility function $v(p_Q, y) \equiv \max_{Q \geq 0} u(Q, y - p_Q Q; 1)$ for a hypothetical consumer with preferences $u(Q, z; 1)$ and facing a linear budget constraint $y = z + p_Q Q$ illuminates the derivations by summarizing relevant features of u.

A. Household Production

I distinguish two broad categories of opioids: prescriptions (Rx, including those diverted into secondary markets or passed through social networks) and illicitly manufactured (Im, especially heroin and fentanyl). On the household production side, Q is a homogeneous function $Q(q_R, q_I)$ of the Rx and Im quantities, respectively, with (at least) the Rx quantities measured in morphine-gram equivalents (MGEs). The units of Q are normalized as $Q(1, 0) = 1$, so that Q's units can also be interpreted as MGEs. Finally, the units of Im are normalized so that $Q(0, 1) = 1$, which means that the scale of Im measurement is proportional to MGEs but the proportionality factor may differ from 1. Im opioids may be more productive than Rx opioids in $Q(\cdot)$ because of intravenous delivery of Im opioids. However, consumers may prefer Rx to Im because Im products may be less uniform and less reliable in terms of potency and use of additives (Galenianos and Gavazza 2017). Intravenous delivery habits are also associated with severe health problems.[6]

The uniformity, reliability, delivery, and other properties of Rx and Im are also reasons why my specification $Q(q_R, q_I)$ allows for the possibility that the two are imperfect substitutes in preferences. The elasticity of factor substitution in Q is not necessarily constant, but it exceeds 1 (so that

[6] These include HIV, hepatitis C, and necrotizing soft-tissue infections (Collier, Doshani, and Asher 2018; Powell, Alpert, and Pacula 2019; May et al. 2021; Hrycko et al. 2022).

purchasing just one of the two is optimal in some circumstances) and exceeds the elasticity of substitution in u. That is, Im is assumed to be a better substitute for Rx than for other goods. A special case of this framework has the function Q as the simple sum of the two quantities, which may be especially relevant for the high-volume consumers whose preferences heavily emphasize morphine-like symptoms over all other goods, consequences, and so on.

Each of the quantities (q_R, q_I) has its own fixed cost (f_R, f_I) and marginal price (p_R, p_I). The marginal prices, representing the quantity of other goods forgone by consuming one more unit of the corresponding opioid, are always positive. A fixed cost is paid for consuming any opioid of a given type, regardless of how much. Particularly relevant for opioid markets is the difference $f_I - f_R$, which tends to be positive because of Im costs of avoiding theft, acquiring self-dosing skills, or overcoming fear of needles. Moreover, because illicit-market prices are typically high and quality low for first-time buyers (Galenianos, Pacula, and Persico 2012; Galenianos and Gavazza 2017), assessing quality and establishing trust with a drug dealer can be fixed costs of accessing a low quality-adjusted price. Depending on market conditions, the marginal price per MGE may be less for Im than for Rx opioids.[7]

The consumer's choice allocates income y among expenditures on other goods z and the fixed and variable costs of obtaining opioids, given $p_R > 0$, $p_I > 0$, $f_R \geq 0$, $f_I \geq 0$ and $y > 0$:

$$\max_{q_R, q_I, \phi, z} u(Q(q_R, q_I), z; \theta), \text{ subject to}$$

$$z \geq 0,\ q_R \geq 0,\ q_I \geq 0,\ z + p_R q_R + p_I q_I + \phi \leq y, \text{ and}$$

$$\phi = \begin{cases} 0 & \text{if } q_R = 0 = q_I, \\ f_R & \text{if } q_R > 0 = q_I, \\ f_I & \text{if } q_R = 0 < q_I, \\ f_R + f_I & \text{if } q_R > 0 \wedge q_I > 0, \end{cases} \tag{1}$$

where ϕ denotes the fixed costs, if any, that the consumer chooses to pay.

LEMMA 1 (Piecewise linear budget constraint). Let $C(Q, p_R, p_I; f_R, f_I)$ denote the minimum expenditure $p_R q_R + p_I q_I + \phi$ required to achieve output $Q \geq 0$, given p_R, p_I, f_R, and f_I and constrained by $Q(q_R, q_I) \geq Q$, $q_R \geq 0$, $q_I \geq 0$, and the four possibilities for ϕ listed in model (1). Then,

[7] The marginal price of morphine symptoms via Im opioids can be low because of intravenous delivery or because the sector is not taxed and spends little on packaging. However, illegal sellers may forgo economies of scale to avoid detection by law enforcement (Campana 2016).

(*a*) $C(Q, p_R, p_I; 0, 0) = QC(1, p_R, p_I; 0, 0) \leq Q \min\{p_R, p_I\}$.

(*b*) The consumer's budget set is $z + C(Q, p_R, p_I; f_R, f_I) \leq y$, $Q \geq 0$, and $z \geq 0$. Its boundary is piecewise linear in the first quadrant of the $[Q, z]$ plane, formed as the upper envelope of the three linear budget constraints corresponding to the three fixed-cost decisions: $y = z + f_R + Qp_R$, $y = z + f_I + Qp_I$, and $y = z + f_R + f_I + QC(1, p_R, p_I; 0, 0)$, respectively.

Proof. Because household production is homogeneous, either one of the cost-minimizing quantities is zero and the other equal to Q or the cost-minimizing ratio q_R/q_I is strictly positive regardless of Q. Either possibility yields the equality in part *a*. Given the unit normalizations, the weak inequality must hold because setting either q_R or q_I to zero is in the feasible set. An allocation $\{Q, z\}$ satisfies the set described in part *b* iff it is part of an allocation satisfying model (1)'s constraints, because C satisfies them by construction. A piecewise linear boundary follows from part *a*. QED

Lemma 1*b* says that the solution to model (1) can be described in two stages. First, the consumer decides how to produce Q from Rx and Im, which is the minimization defining C. Embedded in $C(\cdot)$ are decisions about fixed costs, with each option involving a different constant marginal cost of opioids, $\partial C/\partial Q$. Second, the consumer allocates income y between opioids Q and all other goods according to his preferences $u(Q, z; \theta)$, subject to the constraint $z + C(Q, p_R, p_I; f_R, f_I) \leq y$.

For values of Q nearest zero, the budget constraint involves paying only the lesser fixed cost, if any. If this also has the lowest marginal price, as Rx often did early in the opioid epidemic (especially for those covered by insurance with generous copays), then the greater fixed cost would not be paid, regardless of Q, resulting in a single-segment budget constraint like figure 1*A*'s line through allocation B. At greater quantities, the constraint involves paying the greater fixed cost instead of, or in addition to, the lesser. Either way, the budget set is not convex, because its boundary is steeper at quantities near zero. Overall, the budget constraint may consist of two or three segments, as shown in figure 1*B* and the appendix, respectively.

The segment maximizing $u(Q, z; 1)$ is found by comparing the three values $v(p_R, y - f_R)$, $v(p_I, y - f_I)$, and $v(C(1, p_R, p_I; 0, 0), y - f_R - f_I)$, where v is the aforementioned indirect utility function for a consumer facing a linear budget constraint.[8] Figure 1*A* represents a case with $v(p_R, y - f_R)$ exceeding the other two values, so that all opioid consumption is Rx even at the greater of the two Rx prices shown. Opioid consumption must fall with Rx prices or be a Giffen good. More surprising is figure 1*B*, where $f_R < f_I$ and $v(p_R, y - f_R)$ equals either $v(p_I, y - f_I)$ or $v(C(1, p_R, p_I; 0, 0), y - f_R - f_I)$. Such consumers are indifferent between consuming Rx only (allocation B)

[8] Two or three points simultaneously attain the optimum when some of the values coincide.

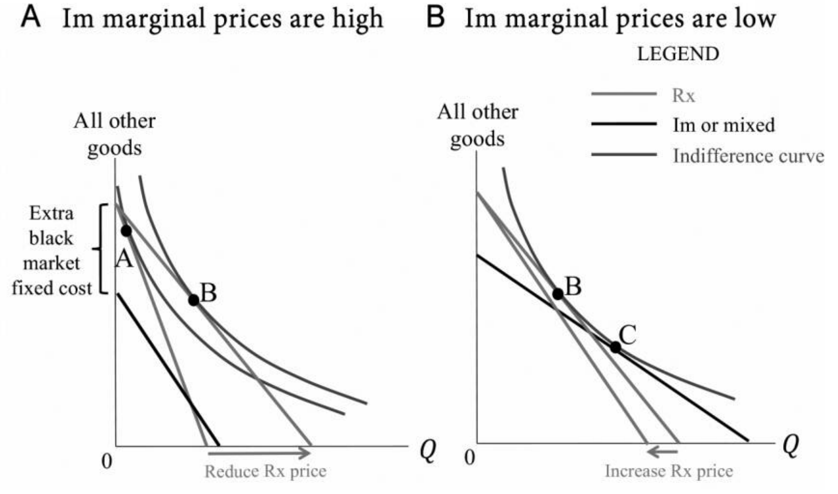

FIG. 1.—Consumption responses to Rx price changes: *A*, Im marginal prices are high; *B*, Im marginal prices are low. Budget lines do not intersect the vertical axis, where the consumption of all other goods would equal income.

and at least some Im, perhaps mixed with Rx (allocation C, where the marginal cost of Q is either p_{I} or $C(1, p_{\mathrm{R}}, p_{\mathrm{I}}; 0, 0)$). If consuming at B, a small increase $dp_{\mathrm{R}} > 0$ in the Rx price results in consuming at allocation C, which has discretely more total opioids and discretely less Rx and all other goods.[9]

The "jump" result for consumers on the margin between budget segments derives from the nonconvexity of the budget set, not from assumptions about income and substitution effects.[10] A marginal increase in the Rx price induces discrete substitution in the Hicksian sense because the consumers stay on the same indifference curve. The amount of substitution in the price dimension is either $p_{\mathrm{R}} - p_{\mathrm{I}} > 0$ or $p_{\mathrm{R}} - C(1, p_{\mathrm{R}}, p_{\mathrm{I}}; 0, 0) > p_{\mathrm{R}} - p_{\mathrm{I}}$, depending on whether the switch is to mixed consumption. This result and the Roy's identity properties of v are essential for what follows.

B. Market-Level Demand

Figure 1 depicts choices by a single consumer type, whereas markets consist of consumers who are heterogeneous in consumption histories, drug tolerance, costs of participating in illegal markets, and other characteristics.

[9] Even in the mixed-consumption case, $dp_{\mathrm{R}} > 0$ cannot induce a jump from C to B because of the elasticity restriction on $Q(q_{\mathrm{R}}, q_{\mathrm{I}})$. A small increase $df_{\mathrm{R}} > 0$ would also induce a jump from B to C, even though it shifts the budget constraint in parallel rather than rotating it.

[10] Related are papers about the Peltzman (1975) effect. Hingson and Kenkel (2004) note that teenagers, facing higher average alcohol prices, are more prone to binge drinking.

For a simple derivation of price effects, the following market-level results take the special case with $f_R = 0 < f_I$, no income effects or mixed consumption, and the preference parameter $\theta > 0$ shifting demand multiplicatively.[11] The appendix shows similar results with income effects and additional heterogeneity.

Let there be a continuum of consumers who differ only in terms of their Im fixed cost f_I. All consumers face the same marginal prices $\{p_R, p_I\}$ and have the same preferences for Q versus other goods. The fraction of consumers with $f_I \le x$ is $F(x) \in [0, 1]$, and the corresponding density function is $F'(x) \ge 0$. Its upper support is denoted $\bar{x} > 0$. Let $\theta f^*(p_R, p_I) \equiv \theta(v(p_I, y) - v(p_R, y))$ denote the critical value of the Im fixed cost that leaves the consumer indifferent between sourcing from Rx and Im. Without income effects on opioid demand, both $f^*(p_R, p_I)$ and the price derivative of v are independent of y. The latter is $-H(p) < 0$, with $H'(p) < 0$, so that the consumer's Hicksian demand function is $\theta H(p)$. It follows that $\theta f^*(p_R, p_I)$ is the area under $\theta H(p)$ between the prices p_I and p_R. The fraction of consumers sourcing from Im rather than Rx is therefore $F(\theta f^*(p_R, p_I))$, with each demanding $Q = \theta H(p_I)$ individually and $D_I = F(\theta f^*(p_R, p_I))\theta H(p_I)$ in aggregate. The remaining consumers demand $Q = \theta H(p_R)$ individually and $D_R = [1 - F(\theta f^*(p_R, p_I))]\theta H(p_R)$ in aggregate. Each proposition that follows assumes that $H(p_I)$ and $H(p_R)$ are strictly positive.

Lemma 2 (Market-level comparative statics). Let $D(p_R, p_I, \theta)$ denote aggregate opioid consumption as a function of the two marginal prices and a common demand parameter θ:

$$D(p_R, p_I, \theta) \equiv F(\theta f^*(p_R, p_I))\theta H(p_I) + [1 - F(\theta f^*(p_R, p_I))]\theta H(p_R). \quad (2)$$

In the neighborhood of $\theta = 1$, the comparative statics of aggregate opioid demand are

$$\begin{aligned} dD(p_R, p_I, \theta)|_{\theta=1} = {} & [1 - F(f^*(p_R, p_I))]H'(p_R)\,dp_R + F(f^*(p_R, p_I))H'(p_I)\,dp_I \\ & + D(p_R, p_I, 1)\,d\theta + (H(p_I) - H(p_R))F'(f^*(p_R, p_I))(H(p_R)\,dp_R \\ & - H(p_I)\,dp_I + f^*(p_R, p_I)\,d\theta). \end{aligned} \quad (3)$$

Proof. Totally differentiate equation (2) and evaluate at $\theta = 1$ to arrive at equation (3). QED

The first line of equation (3) shows the familiar continuous source-specific substitution effects, which are movements along the demand curve $H(\cdot)$ at the two prices, weighted by the fraction of consumers using each source. It also shows the direct effect on market demand of proportional

[11] Without income effects, the indirect utility function has $\partial v/\partial y = 1$ for all prices and incomes. Despite having $f_R = 0$, mixed consumption ($q_R q_I > 0$) is not optimal if Rx and Im are close enough substitutes in $Q(q_R, q_I)$ in the sense defined in the appendix. Income is still represented to the extent it is correlated with f_I, p_R, or p_I.

changes in the component demands $\theta H(p_R)$ and $\theta H(p_I)$. The final term of equation (3) shows effects on total demand of the Rx-Im switching induced by price and demand changes. When $p_R > p_I$, the switching effect of dp_R on total consumption is in the opposite direction as, and potentially of greater magnitude than, the usual movement along the demand curve among those not switching.

The total derivative (3) underpins several testable quantitative insights about opioid demand that are derived by setting to zero one or two of the elements of $\{dp_R, dp_I, d\theta\}$. Technological progress in illicit-opioid manufacturing or the treatment of adverse health effects of intravenous drug use can be modeled as $dp_I < dp_R = d\theta = 0$. Common price reductions $dp_I = dp_R < d\theta = 0$ model technological or policy changes reducing health and other costs of drug addiction.

1. Three Types of Price Changes

Observing the aggregate consequences of any one of the three price changes—$dp_R \neq dp_I = 0$, $dp_I \neq dp_R = 0$, and $dp_R = dp_I \neq 0$—provides quantitative information about the effects of the other two. A powerful result of this type is proposition 1's equivalence in direction and magnitude between effects of a common price change on the composition of opioid consumption and the aggregate-consumption effects of changing either price independently.

Proposition 1 (Equivalence across price changes). Assuming a common demand parameter normalized to 1,

$$\left.\frac{dD_I}{dp_I}\right|_{dp_I=dp_R,\theta=1} = \frac{\partial D(p_R, p_I, 1)}{\partial p_I} \quad \text{and} \quad \left.\frac{dD_R}{dp_R}\right|_{dp_I=dp_R,\theta=1} = \frac{\partial D(p_R, p_I, 1)}{\partial p_R}.$$

Proof. Totally differentiate the definitions of D_I and D_R, and compare with equation (3). QED

A common price change reveals the size and direction of the aggregate effect of ceteris paribus price changes, without observing either one. Conversely, observing the aggregate effect of only one price change reveals the effect of a common price change on that segment. If empirical studies find, say, no Rx consumption decline from a policy increasing p_R and p_I equally, then tighter Rx regulations would not reduce overall consumption. Proposition 1 widens the range of evidence informing specific policies by connecting effects of seemingly different ones.

Proposition 1 is surprising because increasing two prices results in less source switching than increasing just one. However, a switcher affects total consumption less than Im consumption. Hicksian symmetry applied to problem (1) guarantees that the two exactly offset (even at the individual level). Specifically, $H(p_I)$ is both a switcher's Im consumption change and the incentive to switch in response to an Im price change. Also, the gap $H(p_I) - H(p_R)$ is both the incentive to switch in response to a common price change and each switcher's contribution to the aggregate.

Roy's identity provides additional quantitative links between the effects of public policies and technological change that would otherwise appear quite different. Take an increase in Rx regulation (eq. [3] with $dp_R > dp_I = d\theta = 0$), as compared to the effect of cheaper fentanyl ($dp_I < dp_R = d\theta = 0$). The switching term from the Im price change has the same magnitude as the switching term from a Rx price change multiplied by the ratio of Hicksian demands $H(p_I)/H(p_R)$. If Rx regulation induces a lot of switching, then cheaper Im opioids must have an especially large effect on opioid consumption, because a lot of switching reinforces the usual substitution effect.

2. Linking Consumption with Its Composition

Neither common price changes nor changes in the demand parameter are neutral with respect to the composition of opioid consumption. From equation (3), the switching term for a common price change is $-(H(p_I) - H(p_R))^2 F'(f^*(p_R, p_I))dp_I$, which is quadratic in the gap $H(p_I) - H(p_R)$ because the gap reflects both the consumption change of an individual who switches and the change in the incentive to switch. The switching term for a demand shift, $(H(p_I) - H(p_R))(v(p_I, y) - v(p_R, y))F'(f^*(p_R, p_I))d\theta$, has a magnitude with almost the same determinants. Both switching terms are zero when the two prices are equal ($p_R = p_I$) or no consumers are on the source margin ($F' = 0$) but otherwise reinforce the continuous terms. A common price reduction or a demand increase must therefore increase consumption at least as much as they would without switching, especially when the two prices are significantly different. Proposition 2 links overall consumption with its composition.

Proposition 2 (Overall consumption and its Rx share change in opposite directions). Assume that $p_R > p_I$ and $F' > 0$. The comparative statics for opioid consumption $D(p_R, p_I, \theta)$ and the Rx quantity share $r \equiv \{[1 - F(\theta f^*(p_R, p_I))]/D(p_R, p_I, \theta)\}\theta H(p_R)$ have opposite signs if (*a*) $H'(p_I)/H(p_I) - H'(p_R)/H(p_R)$ is sufficiently close to zero and (*b*) the impulse is any one of $dp_I = dp_R \neq 0 = d\theta$ (common price change), $dp_I \neq dp_R = 0 = d\theta$ (Im price change), or $dp_I = dp_R = 0 \neq d\theta$ (preference change).

Proof. From lemma 2 and $p_R > p_I$, a common price reduction, an Im price reduction, or an increase in the demand parameter must each increase $D(p_R, p_I, \theta)$. Totally differentiating the definition of r (see the online appendix) shows that the Im price decrease and θ increase also reduce r. The semielasticity restriction *a* yields the same for a common price increase. QED

With $p_R > p_I$, greater opioid consumption typically increases the benefit from paying the fixed cost of sourcing from Im, and vice versa.[12] The possible exception is when the greater consumption is the result of cheaper Rx prices. More precisely, $\theta f^*(p_R, p_I) > 0$ is the benefit from switching from Rx to Im that would be offset against the fixed cost f_I. As the area under the demand function $\theta H(\cdot)$ between p_I and p_R, $\theta f^*(p_R, p_I)$ can be increased by raising θ, reducing p_I alone, or reducing both prices together. Thus, the three impulses in the proof each induce switching from Rx to Im. The semielasticity restriction a ensures that the comparative statics for r are driven by the direction of switching. If $p_R < p_I$, results would be quite different.

Proposition 2 assumes that the price gap $p_R - p_I$ is positive without restricting its magnitude. However, some of the effects cited have reduced magnitude as the price gap goes to zero. Especially, the preference and common price changes have little effect on r. Changes in F, not treated in proposition 2, would primarily affect r with little effect on overall consumption. With p_R reducing r and (in this range of price gaps) overall consumption, changes in p_R, together with changes in tastes or F, could result in a positive correlation between r and overall consumption. In contrast, at large price gaps, changes in p_R, together with changes in F or any of the impulses cited in proposition 2, result in a negative correlation, because p_R is not reducing overall consumption.

Equation (3) and proposition 2 also suggest that addiction treatment programs reducing θ would not only reduce opioid consumption but also alter its composition. Furthermore, the treatments themselves sometimes involve prescribing (less potent) opioids, such as methadone.

3. Im Price Effects Vary with Rx Prices

The consumption effects of p_I vary predictably with the level of p_R. Proposition 3, its corollary, and proposition 4 offer results of this type.

Proposition 3 (Price interactions in demand). Evaluated at $\theta = 1$, the cross-price derivative of the aggregate-demand function $D(p_R, p_I, 1)$ is

$$\frac{\partial^2 D(p_R, p_I, 1)}{\partial p_R \partial p_I} = \Bigg[F'(f^*(p_R, p_I))\left(\frac{H'(p_R)}{H(p_R)} + \frac{H'(p_I)}{H(p_I)}\right) - F''(f^*(p_R, p_I))(H(p_I) - H(p_R))\Bigg] H(p_R)H(p_I). \tag{4}$$

Proof. Calculate $\partial D(p_R, p_I, 1)/\partial p_I$ from equation (3) and then partially differentiate with respect to p_R. QED

[12] Opioid consumption and several other consumer behaviors involve a kind of increasing returns, namely, that marginal cost falls with the amount consumed (Mulligan 2022b).

The cross derivative (4) is negative unless the density changes sufficiently in the right direction to offset equation (4)'s first term in square brackets. Proposition 3, when used to compare Im price effects across groups with varied Rx access, predicts the group with a higher Rx price to have a more negative Im price effect, all else equal. The corollary gauges this effect's magnitude in the special case with no group density differences ($F'' = 0$), a nonnegative aggregate Rx price effect, and a demand curve that is no more elastic at $H(p_R)$ than at $H(p_I)$.

Corollary (Bounding price-effect differentials). Let POINTSR denote the price elasticity of H evaluated at p_R. If $F'' \geq 0$, POINTSR $\geq p_I H'(p_I)/H(p_I)$, and $\partial D(p_R, p_I, 1)/\partial p_R \geq 0$, then the effect of p_R on the Im price effect is bounded by

$$\frac{\partial^2 D(p_R, p_I, 1)}{\partial p_R \partial \ln p_I} \Big/ \frac{\partial D_R}{\partial p_R} \geq -\left(1 + \frac{p_I}{p_R}\right)\text{POINTSR} > 0. \qquad (5)$$

Applying the corollary does not require measuring the Rx price change, which is challenging when Rx regulations and other factors affect the frictions involved with obtaining Rx opioids for nonmedical use rather than the monetary price itself. The amount of the Rx price change is inferred from the change $\partial D_R/\partial p_R$ in Rx consumption. A stronger and surprising cross-price effect arises by comparing two groups with identical preferences, fixed-cost distribution F, and Im price, but facing different Rx prices. The next section obtains this and additional price effects by formalizing the distinction between the short and long runs.

C. *Price Effects in the Short and Long Runs*

Propositions 1 and 3's comparative statics hold constant the taste parameter θ, but models of habit, addiction, or drug tolerance suggest that demand in the future is affected by consumption now. This can be investigated by modeling a dependence of an individual's taste parameter (recall choice model [1]) on his or her consumption history. An individual with past consumption $\hat{Q}$ and current opioid source that has marginal price p has current consumption $Q = \theta(\hat{Q})H(p)$, where the function $\theta(\cdot) > 0$ has elasticity in the interval [0, 1). I further assume that $Q/\theta(Q)$ covers the range of $H(p)$, supporting the following definition.

Definition (Long-run demand function). For each price $p > 0$, let the long-run demand function $h(p)$ denote the unique solution to $h(p) = \theta(h(p))H(p)$.

Demand is more price elastic in the long run by a factor of $\{1 - [\theta'(h(p))h(p)/\theta(h(p))]\}^{-1} \geq 1$, with equality only when θ is constant.

Suppose for the moment that prices are constant over time, with $p_R > p_I$. Individuals begin the life cycle with no opioid consumption history and low values of θ that increase over time as consumption experience accumulates. Because the choice model (1) predicts that the lowest-θ consumers obtain opioids from the source with less fixed cost—presumably Rx—the model resembles the gateway hypothesis. Namely, young consumers tend to begin opioid consumption with Rx because of their low θ. While Rx-initiated consumers vary in terms of their Im fixed costs, those with common functions $\theta(\cdot)$ and $H(\cdot)$ initially share common life profiles for θ and consumption. Eventually, θ is high enough that lower-fixed-cost consumers switch to Im, which discretely increases opioid consumption, accelerates the life-cycle path for θ, and puts consumption on a path toward the steady-state amount $h(p_I)$. Consumers with relatively high fixed costs may reach the Rx steady state $h(p_R)$ before their θ is high enough to justify switching.

Conditional on functions $\theta(\cdot)$ and $H(\cdot)$, this version of the gateway model results in bimodal steady-state distributions for each consumption and the taste parameter. The fraction of consumers with steady-state consumption $h(p_I)$ is $F(\theta(h(p_R))f^*(p_R, p_I))$, because for them the taste parameter $\theta(h(p_R))$ is enough to justify switching to Im. Steady-state aggregate consumption is

$$h(p_R) + F(\theta(h(p_R))f^*(p_R, p_I))(h(p_I) - h(p_R)). \tag{6}$$

1. The Sign of Rx Price Effects Depends on the Level of Im Prices

Consider two groups with the same preferences $H(\cdot)$ and $\theta(\cdot)$ and the same fixed-cost distribution F facing the same Im price. They differ only in Rx price, with the “low-cost” group paying p_{LO} and the high-cost group paying $p_{HI} > p_{LO} > 0$. Each group’s opioid consumption is bimodal in the steady state, with the group average represented by expression (6) evaluated at the prices paid by its members. While it is unsurprising that the low-cost group might consume more on average, proposition 4 provides conditions where they consume less because of access to lower-priced prescriptions.

Proposition 4 (Group ranks reversed by Im price changes). Fix the Rx prices paid by each group. If

$$\frac{\bar{x}}{\theta(h(p_{HI}))} < \min\left\{\lim_{p_I \to 0} v(p_I, y) - v(p_{HI}, y), \theta(h(p_{LO}))\frac{v(p_{LO}, y) - v(p_{HI}, y)}{\theta(h(p_{LO})) - \theta(h(p_{HI}))}\right\},$$

then

(*a*) At any common Im price no less than p_{HI}, the steady-state average consumption gap between the groups is $h(p_{LO}) - h(p_{HI}) > 0$, with the low-cost group consuming more.

(*b*) There exists another common Im price in the interval $(0, p_{\mathrm{LO}})$ such that the high-cost group consumes more opioids than the low-cost group in the steady state.

Proof. For part *a*, at the assumed Im price, neither group has any member with a benefit from paying the fixed cost. Therefore, each group's steady-state average consumption is on the long-run demand curve $h(p_{\mathrm{R}})$, which involves more consumption for the low-cost group because $h'(p_{\mathrm{R}}) < 0$. Part *b* is proved by example, namely, any value of p_{I} satisfying

$$\frac{\bar{x}}{\theta(h(p_{\mathrm{LO}}))} + v(p_{\mathrm{LO}}, y) > v(p_{\mathrm{I}}, y) > \max\left\{\frac{\bar{x}}{\theta(h(p_{\mathrm{HI}}))} + v(p_{\mathrm{HI}}, y), v(p_{\mathrm{LO}}, y)\right\}.$$

In the steady state, this Im price has all high-cost consumers (facing Rx price p_{HI}) sourcing from Im but leaves at least some low-cost consumers sourcing from Rx. Such a value $p_{\mathrm{I}} > 0$ is guaranteed to exist by the upper-support $(\bar{x})$ restriction. It satisfies $p_{\mathrm{I}} < p_{\mathrm{LO}}$ by construction. Average steady-state consumption is $h(p_{\mathrm{I}})$ for the high-cost group and in the interval $[h(p_{\mathrm{LO}}), h(p_{\mathrm{I}}))$ for the low-cost group. QED

In summary, there exists a change in Im prices that reverses the sign of the gap between the two groups' average steady-state consumption. If fixed costs are not too high, cheap Im opioids induce enough of the high-cost group to source from Im that their average consumption hardly depends on Rx prices. Meanwhile, more of the low-cost group still sources their opioids from Rx. Propositions 3 and 4 have common intuition: lower Im prices expand the range of Rx prices that do not affect an individual's opioid consumption. The proof also reveals that the Im price reduction required to reverse ranks is greater—or may not exist—in populations with high fixed costs or low demand parameter values. The young are an example of at least the latter.

Proposition 4 constrains fixed costs to ensure enough switching as the Im price falls. That limit hardly depends on the taste gap between the two groups, because the second term in the minimum does not bind for taste gaps that are not too large (or zero, as in eq. [3]).

Among the Rx consumers, the low-cost group consumes more and has a greater value of the taste parameter θ. This suggests that previous exposure to cheap Rx increases consumption, even for some time after switching to Im because the switchers in the low-cost group do so with a greater value of θ. But the high-cost group may switch in greater numbers, depending on the Im price. Thus, even the direction of the effect on total consumption of previous exposure to cheap Rx depends on the Im price in relation to Rx prices. This is another way in which the economic model helps anticipate and interpret apparently contradictory behaviors.

Expression (6) describes the steady state in which the Rx price affects the preferences $\theta(h(p_{\mathrm{R}}))$ of those who source from Rx as well as the fraction $F(\theta(h(p_{\mathrm{R}}))f^*(p_{\mathrm{R}}, p_{\mathrm{I}}))$ who source from Im. The short-run effect holds both instances of $\theta(h(p_R))$ constant. Formally, equation (7) for aggregate consumption Δ distinguishes long-standing historical prices $\{\hat{p}_R, \hat{p}_I\}$ from current prices $\{p_R, p_I\}$, with the former determining θ and the fraction of consumers with Im consumption histories and the latter determining switching behavior and source-specific consumption:[13]

$$\begin{aligned}\Delta(p_R, p_I, \hat{p}_R, \hat{p}_I) \equiv\ & \theta(h(\hat{p}_R))H(p_R) + F(\theta(h(\hat{p}_R))f^*(p_R, p_I))\theta(h(\hat{p}_R))(H(p_I) \\ & - H(p_R)) + F(\theta(h(\hat{p}_R))f^*(\hat{p}_R, \hat{p}_I))[\theta(h(\hat{p}_I)) \\ & - \theta(h(\hat{p}_R))]H(p_I).\end{aligned} \tag{7}$$

By analogy with equation (2)'s decomposition of D into D_R and D_I, I define Δ_R and Δ_I to be the Rx and Im components of equation (7), respectively.[14]

In the short run, from the bimodal steady-state consumption distribution, price changes preserve the bimodal taste-parameter distribution but create the trimodal consumption distribution summarized in equation (7). One of the consumption modes is $\theta(h(\hat{p}_R))H(p_R)$, which applies to individuals continuing to source from Rx in the short run when prices are $\{p_R, p_I\}$. A second mode is $\theta(h(\hat{p}_R))H(p_I)$: those sourcing from Rx in the previous steady state but switching to Im. Their fraction of the population is the difference between the two F values shown in equation (7).[15] The third mode is $\theta(h(\hat{p}_I))H(p_I)$ and applies to individuals who continue to source from Im.

The steady-state version of equation (7) is $\Delta(p_R, p_I, p_R, p_I)$, which is identical to expression (6) because long-run demand and short-run demand are related according to $h(p) = \theta(h(p))H(p)$.[16] Equation (7) thereby supports rigorous comparisons of long- and short-run price effects. Propositions 5 and 6 characterize Rx price effects, starting from a steady state with positive Im consumption and $p_R \neq p_I$. That is, both propositions take $\Delta(p_R, p_I, p_R, p_I)$ as a baseline, with the short-run proposition 5 comparing $\Delta(p_R + \rho, p_I, p_R, p_I)$ and the long-run proposition 6 comparing $\Delta(p_R + \rho, p_I, p_R + \rho, p_I)$, for small but positive ρ.

2. Sufficient Statistics Signing Rx Price Effects

As with equation (3), the propositions involve both a movement along the demand curve (either H or h) and a switching term in the other direction as consumers on the source margin switch from Rx to cheaper Im. Both

[13] For brevity, eq. (7) requires that $f^*(p_R, p_I) \geq f^*(\hat{p}_R, \hat{p}_I)$, which includes an increase in p_R or a decrease in p_I compared to their historical values. The online appendix shows that this assumption is unnecessary for the propositions that follow.

[14] Namely, Δ_R and Δ_I are the terms with $H(p_R)$ and $H(p_I)$ coefficients, respectively.

[15] This difference is zero if the area under the short-run demand curve is less under current prices than under historical prices, because those sourcing from Im in the previous steady state were not near the margin of switching back to Rx.

[16] $D(p_R, p_I, \theta)$ (eq. [2]) is itself the special case of $\Delta(p_R, p_I, p_R, p_I)$ in which the taste parameter is independent of past prices and constant across consumers.

propositions identify sufficient statistics for assessing whether the switching term dominates.

PROPOSITION 5 (Sufficient statistics sign the short-run Rx price effect). Defining the short-run cross-price elasticity of Im demand CROSSSR $\equiv (\partial \ln \Delta_I(p_R, p_I, \hat{p}_R, \hat{p}_I)/\partial \ln p_R)|_{\hat{p}_R=p_R,\hat{p}_I=p_I} \geq 0$, the short-run arc elasticity ARCSR $\equiv [1-(H(p_R)/H(p_I))]/[1-(p_R/p_I)] < 0$, and the short-run point elasticity POINTSR $\equiv p_R H'(p_R)/H(p_R) < 0$, the short-run effect of the Rx price on opioid consumption can be signed as

$$
\begin{aligned}
&\operatorname{Sign}\left[\frac{\partial \ln \Delta(p_R, p_I, \hat{p}_R, \hat{p}_I)}{\partial \ln p_R}\Big|_{\hat{p}_R=p_R,\hat{p}_I=p_I}\right] \\
&\quad = \operatorname{Sign}\left[\frac{1-r}{r}\,\text{CROSSSR}\,\frac{\text{ARCSR}}{\text{POINTSR}}\left(\frac{p_R}{p_I}-1\right)-1\right].
\end{aligned}
\tag{8}
$$

Proof. Evaluate the partial derivative of equation (7), eliminating $F(\cdot)$, $F'(\cdot)$, $H(p_R)$, $H'(p_R)$, and the price derivative of v using Roy's identity and the definitions of r, CROSSSR, ARCSR, and POINTSR. Factoring out the positive factor $(-r\,\text{POINTSR})$ yields equation (8). QED

The switching term derived from equation (7) is the product of a density $F'(\cdot)$, a taste parameter, and the horizontal distance $H(p_I) - H(p_R)$ between the two allocations in figure 1*B*. In equation (8), CROSSSR represents the density effect, while the product of ARCSR and the relative price term summarizes the horizontal distance. As p_R increases enough beyond p_I, either the switching term dominates or there are no longer any consumers on the margin between sources. In the first case, p_R reaches a level at which total demand slopes the "wrong" way (more consumption at high prices) even though the preference function u satisfies the usual quasi-concave assumptions. The aggregate-consumption equations (2) and (7) are akin to a tax revenue Laffer curve, which also must slope the "wrong" way for tax rates that are extreme enough.

Given p_I, the consumption-minimizing prescription price is above p_I but finite. Because the minimizing p_R sets both sides of equation (8) to zero, it increases with p_I and r. In other words, if p_I and r were to fall with additional illicit supply, Rx policy seeking to minimize consumption must reduce p_R in a greater proportion than p_I did, unless the behavioral elasticity term CROSSSR(ARCSR/POINTSR) happened to change significantly.

Equation (8) indicates whether the demand jump $H(p_I) - H(p_R)$ is large enough for the switching consumers (the price gap term) and whether enough consumers are switching (the r and CROSSSR terms) to compensate for the reduced demand of those staying with Rx. Near $p_R = p_I$, aggregate consumption must slope down with p_R because the switching term is zero. As the statistics featured in equation (8) vary over time, across regions, between demographic groups, or between market segments, the magnitude and sign of p_R's short-run effect vary, albeit predictably. Empirical estimates from one context do not necessarily indicate even the direction of the effect in other contexts, but they can when viewed through the lens of equation (8).

Further interesting comparative statics from equation (7) with $p_R > p_I$ are the effects of the past Rx price $\hat{p}_R$, holding constant the other three prices. If $\hat{p}_R \leq \hat{p}_I$, then cheaper Rx in the past ($d\hat{p}_R < 0$) not only increases total opioid consumption in the present but must also increase present Im consumption. This result is also consistent with the gateway hypothesis, because the legacy of cheaper Rx in the past is a strong preference for opioids in the present, which both encourages switching to cheaper Im in the present and consuming more, conditional on source. In contrast, propositions 4 and 6 consider permanent changes in Rx prices, which can be understood as combining changes in the past price with an equal change in the current price. Not surprisingly, the current price can matter more for present behavior than the past price does.

The taste parameter θ may increase over the life cycle as addiction or tolerance builds, thereby increasing a cohort's Im intensity $(1 - r)/r$. Im intensity also increases with age to the extent that fixed costs of Im consumption fall as youth are less supervised by adults as they age. Either way, proposition 5 suggests that the short-run effect of increasing p_R might be negative among children and youth while positive among adults. Proposition 6 considers the long-run effect.

PROPOSITION 6 (Sufficient statistics sign the long-run Rx price effect). Defining the long-run cross-price elasticity of Im demand CROSSLR $\equiv d \ln \Delta_I(p_R, p_I, p_R, p_I)/d \ln p_R$, the long-run arc elasticity ARCLR $\equiv [1 - (h(p_R)/h(p_I))]/[1-(p_R/p_I)] <$ ARCSR, and the long-run point elasticity POINTLR $\equiv p_R h'(p_R)/h(p_R) <$ POINTSR,

(*a*) The long-run effect of the Rx price on opioid consumption can be signed as

$$\mathrm{Sign}\left[\frac{d \ln \Delta(p_R, p_I, p_R, p_I)}{d \ln p_R}\right] = \mathrm{Sign}\left[\frac{1-r}{r}\mathrm{CROSSSR}\frac{\mathrm{ARCLR}}{\mathrm{POINTLR}}\left(\frac{p_R}{p_I} - 1\right) - 1\right]. \tag{9}$$

(*b*) The Rx price can reduce opioid consumption in the long run even when it increases it in the short run.

Proof. For part *a*, evaluate the p_R derivative of expression (6). Eliminate $F(\cdot)$, $F'(\cdot)$, $H(p_R)$, $H'(p_R)$, and the price derivative of v using Roy's identity and the definitions of r, CROSSLR, ARCLR, and POINTLR. Factoring out the positive factor ($-r$ POINTLR) yields equation (9). Part *b* is proved by example, where p_R exceeds p_I enough for Rx prices to increase consumption in the short run but the effect of past consumption on tastes satisfies

$$\theta'(h(p_R)) = [H(p_R) - (v(p_I, y) - v(p_R, y))H'(p_R)/H(p_R)]^{-1} \in (0, \theta(h(p_R))/h(p_R)).$$

Rx prices must reduce steady-state consumption in this case because CROSSLR is zero. QED

From expression (6), Rx prices affect steady-state Im consumption only through switching. In the short run, the switchers have a taste parameter that reflects their Rx history and thereby consume less than incumbent Im consumers do. In the steady state, that Rx history no longer matters. This effect tends to make CROSSLR > CROSSSR. On the other hand, past Rx prices reduce the value of switching by reducing current Rx demand through the taste parameter. This steady-state gateway effect can be strong enough to make CROSSLR zero or negative, which means that the high Rx prices early in the life cycle sufficiently discourage opioid habits to reduce the fraction of a cohort that ever switches to Im. The proof of proposition 6*b* offers the example in which the effect of past prices has exactly the magnitude required for CROSSLR = 0.

As a function of p_R, the steady-state expression (6) is also analogous to a Laffer curve, with total opioid consumption falling with p_R at low values but potentially reaching a consumption minimum beyond which point p_R changes consumption in the other direction. Proposition 6 indicates which of the two cases applies. A small Rx share tends toward the "wrong" side of the Laffer curve, because the movement along the long-run demand curve $h(p_R)$ applies to only a small market segment. Especially, a large price gap $p_R - p_I$ tends that way because it increases the amount that each switcher changes consumption by gaining access to Im opioids with low marginal prices.

Proposition 4's steady-state rank-reversal result is a discrete Rx price effect closely related to the marginal Rx price changes addressed by proposition 6. Namely, proposition 4*a* can be illustrated as two groups facing similar, but distinct, Rx prices on the intuitive part of the aggregate-demand curve where equation (9) has a negative sign. Proposition 4*b* says that a sufficient reduction in Im prices for both groups moves them to the "wrong" side of the curve, reversing the sign of equation (9). Both groups consume more opioids than they would at higher Im prices, but between the two groups the low-cost group consumes less.

For additional understanding of proposition 4*b*, let us assume that Rx restrictions induce enough substitution to Im opioids to increase overall opioid consumption (see also sec. IV). If the Rx restrictions solely affect the Rx price, then two groups differing only by Rx price would have more average consumption for the high-cost group. In this way, model (1) links two seeming unrelated observations: (i) that opioid consumption, at times, increases with Rx prices and (ii) a group consumption gap that changes sign in the same instances.

III. Quantity, Policy, and Price Measures

Proxies for quantities of opioids consumed, opioid policies, and opioid prices are necessary to test the theoretical predictions. Quantity data are essential because many of the predictions regard consumption rather than prices. Price and policy indicators help partition the recent history of opioid markets into distinct phases in terms of the direction of significant price changes (see also CEA 2019 and Powell and Pacula 2021).

A. *Opioid Fatalities*

Annual fatalities by region and demographic group are measured for 1999–2021 using the online CDC-WONDER (Wide-ranging Online Data for Epidemiological Research) tools, sponsored by the Centers for Disease Control and Prevention (CDC), for tabulating every death certificate filed with a state or the District of Columbia (essentially every death in the country). Each death certificate "contains a single underlying cause of death, up to twenty additional multiple causes, and demographic data" (CDC 2022). The tools permit tabulation by any of the thousands of underlying causes or by selected cause groups, such as "drug-induced causes." Death certificates can additionally be tabulated by any of the thousands of (more specific) multiple causes, such as unintentional heroin poisoning. I select only records where the underlying cause of death is drug-induced causes, which are primarily ICD-10 (International Classification of Diseases, 10th revision) codes X40–X44, X60–X64, X85, and Y10–Y14. I further limit records to those where opioids are listed as immediate or contributory causes of death (ICD-10 T codes 40.0/opium, 40.1/heroin, 40.2/other, 40.3/methadone, and 40.4/synthetic). Opium, heroin, and "synthetic" are treated as Im opioids and the other two T codes as Rx opioids. For measuring annual fatality rates by demographic group or for the nation, I use population estimates from the CDC-WONDER tools. The all-race analyses use the nine census divisions, gender, and three age groups.[17] Solely for estimating shares, any death certificate indicating both Rx and Im opioids is considered both a Rx death and an Im death. Because of CDC-WONDER's cell-size limits and because proposition 4 refers only to overall opioid consumption, race comparisons pool Rx and Im fatalities.[18]

[17] The age groups are 0–44, 45–64, and 65+. The regional divisions are shown in table 1.

[18] For the all-races analyses, which involve the ratio of Rx-opioid deaths to Im-opioid deaths, CDC WONDER's minimum-cell-size limits result in only eight cells (of 1,242) with missing mortality data, and those are limited to the years 2000 and 2001 in the East South Central region. Race comparisons are conducted for the years 2012–21, when there are no missing data at the division by gender by age group by year level after 2013 and only 12 (of 216) cells with missing data for 2012 or 2013.

TABLE 1
Death Certificate Summary Statistics

Census Division	Black Population (%)[a]	Opioid Deaths per 100,000			Rx Share of Opioid Deaths		
		1999–2012	2013–21	Change	1999–2012 (%)	2013–21 (%)	Change (pp)
New England	8	4.8	24.3	19.5	62	21	−40
Middle Atlantic	17	3.5	17.0	13.6	57	25	−32
East North Central	13	4.0	18.9	14.9	57	24	−33
West North Central	8	3.5	9.2	5.7	65	33	−33
South Atlantic	24	5.6	16.8	11.2	74	31	−42
East South Central	21	4.7	16.7	12.0	81	35	−46
West South Central	16	4.0	6.6	2.5	69	40	−29
Mountain	5	7.1	13.2	6.1	74	43	−31
Pacific	8	4.6	8.4	3.8	70	37	−34
US total	15	4.6	14.1	9.5	68	30	−38

Note.—Death certificates indicating both Rx and Im opioids count as both for the purposes of calculating percentages. pp = percentage points. Source: CDC WONDER.
[a] Percentage of black + white.

I assume that within age and gender and year, the opioid fatality rate is proportional to MGEs consumed, so that predictions about consumption are also predictions about mortality within age/gender/year. An earlier version of this paper (Mulligan 2020) showed that, while illicit fentanyl is more MGE intensive, the national changes over time in the MGEs of fentanyl seized by law enforcement (perhaps a consumption proxy) closely follow the number of death certificates indicating that fentanyl was involved in a drug-induced death.

The first two columns of table 1 list census divisions and their relative populations of whites and blacks. The remaining columns show opioid death rates and prescription shares of opioid deaths separately by subperiod. Death rates increased substantially, although their levels and changes varied considerably across geography. The differential changes are often attributed to differential penetration of illicit opioids by geography. Also note that census divisions with the greater death rate increases tend to be those with more blacks, relative to whites.

B. *Federal Policy Database*

Although the OxyContin reformulation receives much attention in the literature, it helps to know its relation with other policies since 2000 that might affect the price or accessibility of opioids for nonmedical use. The model distinguishes Rx policies from Im policies.[19] With the former

[19] See also the Savona, Kleiman, and Calderoni (2017) compilation of criminology studies of parallel legal and illicit drug markets.

more numerous, I further partition Rx policies along the chain of production, distinguishing prescribing from consumer effort and expenditure.

As detailed in the online appendix, policies were identified from Federal Register final rules and from Department of Justice press releases for the years 2001–19, using the search criterion "opioids." A rule was eliminated if I deemed it insignificant or if it set policy unrelated to the price, cost, or availability of opioids, such as a 2011 rule changing the name of an advisory committee. Five rules implemented or significantly changed prior rules, agency documents, or statutes, in which case I located and included those prior policies. The results shown in table 2 suggest that regulatory and fiscal activity is higher for Rx than for Im. In the earlier years, opioid subsidies are created and expanded for patients and prescribers, while regulations are relaxed. In about 2010, policies begin to swing in the other direction, as with the reformulation (see below) and programs discouraging prescription supply to secondary markets. The results also suggest that enforcement of illicit-drug prohibitions was less of a priority between 2013 and 2016.

C. *Opioid Price Structure*

The key premises about opioid prices in this paper are that (i) heroin was significantly more expensive per MGE than Rx opioids in the 1990s, (ii) Im opioids became cheaper over time, especially since 2013, and ultimately cheaper than Rx opioids, and (iii) beginning in about 2011, Rx opioids became more expensive or difficult to access for nonmedical use as a result of regulatory and fiscal changes. These hypotheses motivate the analysis and interpretation of the quantity data, without relying on more precise characterization of prices in opioid markets where participants have strong incentives to avoid being measured.

On premises i and ii, market participants have described a per-dose price gap between heroin and Rx opioids that changed from significantly positive in the 1990s to significantly negative in the late 2010s. Rx opioids were once known as "hillbilly heroin" or "poor man's heroin" (Butterfield 2001; Jayawant and Balkrishnan 2005; Quinones 2015). Heroin was later recognized to be the cheaper alternative (Cicero et al. 2014; Cicero, Ellis, and Kasper 2017; National Academies 2017). In a recent survey of opioid addiction treatment patients, "almost all—94 percent—said they chose to use heroin because prescription opioids were 'far more expensive and harder to obtain'" (NIDA 2018).

An earlier version of this paper (Mulligan 2020) identifies the year 2013 as a turning point for both survey reports of ease of heroin access and the share of illegal contraband arriving in crime labs that was fentanyl or heroin. Before then, Im fentanyl was largely absent from the drug supply, with the exception of brief localized episodes that ended with a shutdown of the source by law enforcement. Afterward, consumers frequently received heroin mixed—some would say adulterated—with fentanyl. Fentanyl "is phenomenally inexpensive per dose in wholesale markets" (Pardo et al. 2019, 119) and cheap enough to largely displace heroin from illicit markets, as it has done in some countries and regions of North America.[20] Likely explanations include technological advances among illicit manufacturers—perhaps to be expected, given the synthetic revolution in other erstwhile agricultural markets such as fertilizers—and new smuggling opportunities.

Nonmedical opioid users often crushed or dissolved prescription pills for injection or snorting (contrary to the prescribed method). In response, the Food and Drug Administration (FDA) in 2010 approved new "abuse-deterrent formulation" opioids, which are not abused as easily. This amounted to an increase in the full price of nonmedical Rx opioid use. As shown in table 2, from 2010 onward, fiscal and regulatory policies discouraged nonmedical use of Rx opioids, which can be modeled as increases in p_R and perhaps also f_R. Kim (2021) and others show that opioid behavior was affected by new state-level "prescription drug monitoring" requirements for prescribers to check patient-history databases, most of which were implemented in 2012–14.

IV. Empirical Findings by Age, Geography, and Race

Much previous research makes a strong case that substitution between medical and illicit opioid markets has been substantial enough that at times the demand for opioids has been increasing in the price of Rx opioids. This paper shows what the previous findings may reveal about additional consequences of technological and regulatory changes in opioid markets, as presented by propositions 1–6. This section tests those four of the predictions that can be evaluated without precise measures of the magnitude of price changes or data that span multiple generations. Specifically, the death certificate data are used to assess whether the sign of the relationship between overall death rate and its composition changed over time; whether as Rx supply was restricted after 2010, opioid deaths fell for children and youth, whose opioid consumption appeared to be especially Rx intensive; and whether the opioid death rate for blacks surpassed the rate for whites, especially among middle-aged and older people, during the more recent period, when it appears that Im prices fell sharply (premise ii).

[20] See Pardo et al. (2019, 20ff., 109–36) on British Columbia, Estonia, and Latvia. Mortality and National Forensic Laboratory Information System data suggest that this had also occurred in most of the northeastern United States by 2019.

TABLE 2
Changes in Federal Incentives Related to the Market for Opioids

Year	Incentives for: Prescribers	Patient Rx Purchases	Illicit Manufacture
2000	VHA mandates "5th Vital Sign"[a]		
2001	Pain management becomes part of Medicare/Medicaid accreditation (CMS delegated to TJC)[b]		
2005	DEA clarifies that opioid refills are not permitted but that subsequent prescriptions can be obtained without appointment[c]		
2006		Medicare Part D begins covering opioids, but not benzos (CMS)[d]	Fentanyl manufacturing shutdown; DEA prohibitions follow[e]
2007	DEA allows multiple prescriptions with a single office visit;[f] CMS publicizes and requires quality measures, including HCAHPS pain questions, for full reimbursement[g]		
2010	DEA allows electronic Rx[h]	First DEA Rx take-back programs[i]; product reformulation and withdrawal (FDA)[j]	
2012	CMS penalizes low HCAHPS scores[k]		
2013	VHA Opioid Safety Initiative; peak VHA opioid Rx[l]	Medicare Part D begins covering benzos too (CMS).[m]	Holder memo: DOJ does not prosecute nonviolent drug crimes[n]
2014	DEA switches hydrocodone combination products from Schedule III to Schedule II[o]	Medicaid expansion; deadline for other insurance to cover benzos (ACA)[p]	
2017	CMS changes its use of pain management surveys[q]	FDA first requires benzos to carry an opioid interaction warning[r]	Holder memo reversed[s]

2018	Rx quotas tightened[t]	SUPPORT Act[u]	SUPPORT Act[u]
2019	CMS removes pain management questions from HCAHPS[v]		Series of new DEA prohibitions[w]

NOTE.—CMS = Centers for Medicare and Medicaid Services; TJC = The Joint Commission (on Accreditation of Healthcare Organizations); DEA = Drug Enforcement Administration; benzo = benzodiazepine; HCAHPS = Hospital Consumer Assessment of Healthcare Providers and Systems; VHA = Veterans Health Administration; DOJ = Department of Justice; ACA = [Patient Protection and] Affordable Care Act; SUPPORT Act = Substance Use Disorder Prevention that Promotes Opioid Recovery and Treatment for Patients and Communities Act.

[a] Department of Veterans Affairs (2000).

[b] JCAHO (2001). See also 66 FR 4076.

[c] DEA (2005).

[d] 70 FR 4228 (January 2005).

[e] DEA prohibits fentanyl ingredients in 2008 (73 FR 43355) and 2010 (75 FR 37295).

[f] DEA (2007).

[g] 71 FR 68193 (November 2006).

[h] DEA. 75 FR 61613 (October 2010).

[i] DEA (2010).

[j] https://www.medpagetoday.com/productalert/devicesandvaccines/19409 and https://www.fda.gov/drugs/drug-safety-and-availability/fda-drug-safety-communication-fda-recommends-against-continued-use-propoxyphene.

[k] “Medicare Program; Hospital Inpatient Value-Based Purchasing Program” CMS, May 6, 2011 (76 FR 26493).

[l] Good (2017).

[m] 77 FR 22076 (April 2012).

[n] Holder (2013).

[o] “Schedules of Controlled Substances: Rescheduling Hydrocodone Combination Products from Schedule III to Schedule II.” DEA, August 22, 2014 (79 FR 49661).

[p] Benzo coverage is in Sec. 2502 of the Patient Protection and Affordable Care Act.

[q] Effective October 2017, the pain part of HCAHPS would no longer be used for the Value-Based Purchasing Program, although still for accreditation (81 FR 79571). Effective October 2019, outpatient departments would participate in their version of HCAHPS (OAS [outpatient and ambulatory surgery] CAHPS; 71 FR 79771).

[r] https://www.fda.gov/drugs/information-drug-class/new-safety-measures-announced-opioid-analgesics-prescription-opioid-cough-products-and.

[s] Sessions (2017).

[t] 83 FR 32784 (July 2012).

[u] SUPPORT criminalized possession of controlled-substance analogs, restricted illicit import, and encouraged unused-Rx disposal.

[v] 83 FR 58820.

[w] Spanning May 2016 through November 2019, 11 DEA rules put various fentanyl analogs on Schedule I.

A. *Segment Shares and Opioid Deaths across Areas and over Time*

If geographic areas differ from each other primarily in terms of Im opioid prices, the level of opioid demand at a given price, or both, then the cross-geographic relationship between the overall opioid death rate and its composition depends on the sign of the price difference $p_R - p_I$ present in a typical area (proposition 2). This result also holds for geographic differences in the distribution F of fixed costs and, if the price difference $p_R - p_I$ is positive enough, for differences in the Rx price.[21] Specifically, to the extent that the admittedly sparse price data suggest that $p_R - p_I$ is negative or close enough to zero in many of the years before 2010 and enough greater than zero in many of the years after, then the relatively high-consumption areas would be Rx intensive in the early years but Im intensive later. To investigate this, I estimate the following linear regression:

$$\ln m_{a,d,g,t} = \alpha_{a,g,t} + \beta_t r_{a,d,g,t} + \varepsilon_{a,d,g,t}, \tag{10}$$

where m denotes the opioid mortality rate and a, d, g, and t denote age group (0–44, 45–64, 65+), census division, gender, and year, respectively. Following equation (8), equation (10) denotes the share of opioid deaths involving Rx opioids as r; $\alpha_{a,g,t}$ is a full vector of interaction terms; $\varepsilon_{a,d,g,t}$ is the error term. The mortality rate proxies for opioid consumption, but the log specification and the interaction vector allow fatalities per quantity consumed to vary by age, gender, and year. Because, in theory, both m and r reflect price changes rather than one causing the other, the online appendix shows alternative measures of cross-area correlation and Rx share, with similar results.

Each year t has 53 or 54 age/gender/census-division cells used to estimate the regression coefficient β_t.[22] Figure 2 shows point estimates and confidence intervals. The cross-area relationship between opioid deaths and their Rx intensity changed from positive to negative in about 2012 or 2013. A sign change sometime during the period 1999–2021 is consistent with proposition 2. However, without more precise price estimates, we do not have a prediction as to the exact date. These findings do not rule out alternative explanations for the sign change.

[21] Geographic differences in law enforcement, regulation, "pill mills" (Mallatt 2018; Schnell 2018), or the penetration of prescription-subsidy programs (Soni 2018) may create geographic differences in Rx prices or the distribution of fixed costs for engaging in illicit markets. Differential availability of drug treatment contributes to geographic differences in θ.

[22] Each of the 54 cells is weighted by its total opioid deaths in 1999–2021. For each of 1999, 2000, and 2002, one cell (with less than 1/800 the weight of the rest of the year's data) is omitted from the regression because of zero opioid deaths. The online appendix shows that including the opioid fatality rate in levels instead of logs does not change fig. 2's basic pattern.

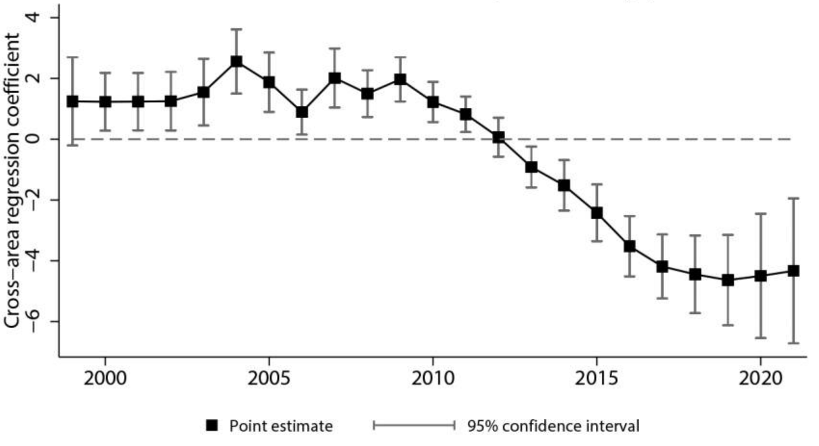

FIG. 2.—Cross-area relation between opioid death rates and their Rx-Im composition, by year. Observations are age group by gender by census division. Each year, log opioid deaths per 100,000 is regressed on gender–age group interactions and the Rx share of opioid deaths, weighting by total opioid deaths 1999–2021. The horizontal axis is shown as a dashed line. Source: CDC WONDER.

B. *The Differential Effects by Age of Restrictions in Nonmedical Rx Supply*

In about 2010, OxyContin's reformulation and government regulations restricted nonmedical Rx supply. Previous studies of the resulting substitution to Im opioids find that it may have been enough to keep overall opioid mortality about constant.[23] In terms of the sufficient-statistics results, equation (8) evaluates to about zero for the overall population at that time but to less than zero for groups with Rx-intensive opioid consumption, such as children and youth.[24]

The literature on the consequences of OxyContin's reformulation does not estimate separate empirical models by age, while the experiences of minors contribute little to the estimates. An exception, Alpert, Powell, and Pacula (2018), finds different effects through the year 2013 on the heroin fatality rate among persons aged 0–24 but does not indicate whether the group's overall opioid fatality (Rx and Im) fell. Instead,

[23] Ruhm (2019a, 27) concludes that "the release of an abuse-deterrent formulation of OxyContin in 2010 reduced [Rx] demand but almost certainly fueled some substitution to heroin." Alpert, Powell, and Pacula (2018) and Evans, Lieber, and Power (2019) find that reformulation reduced Rx deaths and increased Im deaths, leaving total deaths about constant. See also Mallatt (2018). Wolff et al. (2020) do not find increased heroin initiation rates among survey respondents related to misusing OxyContin before reformulation. Kim (2021) finds that state-level Rx regulations resulted in substantial substitution to Im opioids.

[24] Mulligan (2020) finds that the Rx share of opioid deaths falls with age at least until age 18.

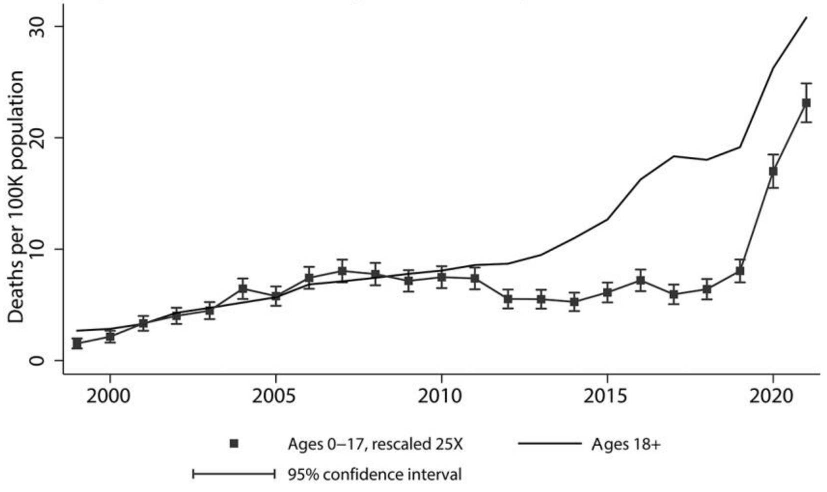

FIG. 3.—Opioid fatality rates among minors and adults. The mortality rate for minors is multiplied by 25 to show on the same scale with adults. Adult confidence intervals are not shown because they are less than 0.5 per 100,000. Population and mortality source: CDC WONDER.

my figure 3 specifically focuses on the mortality of minors, showing the more familiar adult series as a reference. The two series exhibit similar patterns until about 2011, after which significant gaps emerge.[25] Because the minors' series remains below its 2010 values for several years, stricter prescription policies may have reduced fatalities among minors, even with falling Im prices and other fatality-increasing factors.[26]

Figure 3 also shows opioid mortality accelerating during the COVID-19 pandemic. Mulligan (2022a) calibrates a dual-source substance-abuse model, derived from equation (2), to forecast monthly drug and alcohol mortality beginning in early 2020. The model also predicts how alcohol-related causes, narcotics, and methamphetamine would each contribute to the excess mortality. The mortality surge during the pandemic coincides with switching from drinking at bars and restaurants to cheaper alcohol at home as well as opioid switching from Rx to cheaper Im sources.

With the data having both geography and year dimensions, the connection between these supply changes and the adult-minors gap in overall opioid mortality can be further investigated in an event-study framework.

[25] From the perspective of a binomial mortality model, let m_t be the point estimate of the year t probability of a fatal opioid overdose. Figure 3's 95% confidence interval around the point estimate is $m_t \pm 1.96[(1 - m_t)m_t/n_t]^{1/2}$, where n_t is the number aged 0–17 in year t. Confidence intervals are not shown for the adult series because they are small on the scale of fig. 3.

[26] Mulligan (2020) uses national data to look at more detailed age categories, finding that much of the age gradient in mortality and its composition occurs before age 22.

This approach has much in common with Alpert, Powell, and Pacula (2018) and Kim (2021), except that they focus on heroin mortality for the entire population rather than the difference between adults' and minors' all-opioid mortality that is of interest here. The online appendix provides the details as to the policy measures, econometric specifications, and comparisons with previous studies. The overall findings are that (i) the timing of the widening of the adult-child mortality gap in a geographic area is related to the timing of its adoption of Rx regulations and (ii) the amount that the mortality gap widens tends to be greater in areas that were more "exposed" to OxyContin's reformulation. Furthermore, the estimates suggest that much of the gap in figure 3 between 2010 and 2016 may be explained by Rx restrictions, which were implemented almost entirely during that timeframe. More work is needed to determine whether reduced opioid use among minors was enough to eventually reduce adult mortality even if Rx restrictions did not have that effect in the short run.

C. *The Rank Reversal of Blacks and Whites*

Since the early 2000s, scholars have observed lower opioid death rates for blacks than for whites. Case and Deaton (2020, 65) report that "blacks were not suffering the epidemic of overdoses, suicide, and alcoholism." Although expecting fentanyl to narrow the race gap, Case and Deaton attribute much of the gap to black communities' "disgust" with 1980s crack addiction as well as other factors resulting in lower suicide rates for blacks. However, if much of the early-2000s race gap was due to differential Rx access, the possibility of substitution between Rx and Im has strong predictions for how the gap would evolve as Im opioids became cheaper.[27] Especially, proposition 4 predicts that, with a persistent race gap in Rx access, falling illicit-opioid prices would eventually push the black death rate past the white rate. The race mortality gap would reverse in older populations with less of an Im price change because of the additional time they had to accumulate complementary human capital and to develop addiction and tolerance.[28]

Figure 4 displays time series of the black-white gap in opioid fatality rates from 2012 to 2021. In each cross section of persons alive at the beginning of the year, the gaps are adjusted for gender, age group (0–44, 45–64, and 65+), and census division by regressing an opioid fatality indicator on

[27] A number of studies found lower opioid-prescribing rates as well as less health-insurance coverage for black patients, both of which may have affected the price and availability of Rx opioids (Todd et al. 2000; Lowe et al. 2001; Pletcher et al. 2008; Buchmueller and Levy 2020; Rambachan et al. 2021).

[28] A medical literature refers to "acquired behavioral tolerance," in which patients form behavioral habits to help reduce nonpecuniary costs of drug exposure (Dumas and Pollack 2008).

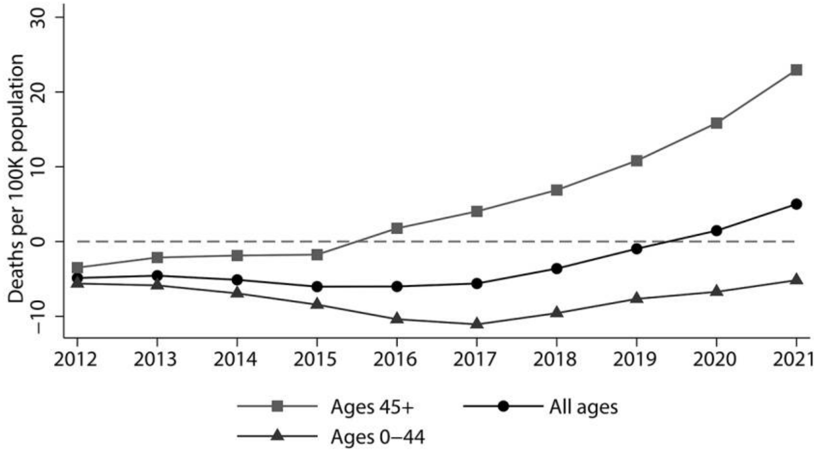

FIG. 4.—Black-white gaps in opioid fatality rates, adjusted for gender, age group, and census division. For each year, an opioid death indicator is regressed on indicators for race, gender, age group, and census division, with 100,000 times the black coefficient shown in the figure. A regression observation is a black or white US resident alive on January 1. Gap confidence intervals (not shown) are less than 2 per 100,000 population. Population and mortality source: CDC WONDER.

indicators for those three variables as well as race, whose rescaled coefficient is the gap shown in the figure. The census-division adjustment is meaningful because black population shares and the recent increase in fentanyl deaths are positively correlated across areas. When the sample is limited to persons aged 45+, the adjusted race gap reverses by 2016, whereas as recently as 2021 the black rate remains lower among persons under age 45.[29]

The magnitude of the race gap change predicted by the corollary to proposition 3 is significant on the scale of the actual change, although not necessarily explaining all of it. For example, consider a point elasticity of −0.5, Im opioid prices that fell by a factor of 3 after 2013, and that differential Rx access was enough to put the initial Rx mortality rate gap at 4 per 100,000. Inequality (5) predicts a change in the overall opioid death rate for blacks that exceeds the white change by at least 4.4 (per 100,000).[30] By comparison, figure 4 shows a differential change of 3.9 from 2012 through 2019 and 9.9 through 2021.

[29] Race gap standard errors are less than 0.5 per 100,000 population, as expected, given that the black population is about 40,000,000 and that in most years blacks' opioid death rate exceeds 2 per 100,000. Note that opioid initiation is common even past age 30 (Ellis, Kasper, and Scroggins 2021).

[30] That is, $4.4 = 4 \times [(1 + 1)(-0.5)] \times \ln(1/3)$, where the term in square brackets is the numerical counterpart to the right-hand side of inequality (5).

An alternative explanation for the race reversal is that nonopioid drugs, more commonly used among blacks, are increasingly adulterated with fentanyl.[31] The distribution F of fixed costs might also differ between the races, especially as it relates to the distribution of income or opportunity costs. COVID-19 pandemic disruptions of employment, medical care, and so on may also be relevant. While more research is needed for a complete quantitative model of black-white differences, the results suggest that the Rx-Im substitution patterns observed in connection with the reformulation of OxyContin and implementation of Rx regulations may economically mirror the forces pushing blacks' death rate beyond whites'.

Although not examining race gaps, previous studies have, in two ways, linked Im opioid mortality after 2010 with high Rx consumption before 2010. One finding is that states with "triplicate" Rx regulations had low Rx mortality early on and were subsequently "less affected by transitions to illicit drugs" (Alpert et al. 2022, 1164). This connection resembles the conceptual experiment $(\partial\Delta_{\mathrm{I}}(p_{\mathrm{R}}, p_{\mathrm{I}}, \hat{p}_{\mathrm{R}}, \hat{p}_{\mathrm{I}})/\partial\hat{p}_{\mathrm{R}})|_{\hat{p}_{\mathrm{R}}\le\hat{p}_{\mathrm{I}}, p_{\mathrm{R}}>p_{\mathrm{I}}}$ because the regulation was "discontinued . . . by 2004" (1148; before Im opioids became so cheap). It is perhaps unsurprising that opioid mortality remained below the national average in those states because of a negative effect of past Rx prices on current consumption. However, if the regulation significantly increased the full price of prescriptions and had persisted well beyond 2010, the experiment would resemble my proposition 4. In that hypothetical, the triplicate states would have been more affected by the drop in Im prices that occurred during the 5–10 years after 2010.

A second set of findings is that increases after 2010 in Im-opioid mortality, and ultimately overall opioid mortality, were less in states with low "rates of OxyContin misuse . . . in the pre-reformulation period" (Alpert, Powell, and Pacula 2018, 13; also Powell and Pacula 2021). Whereas triplicate regulation status is plausibly understood as a proxy for full Rx prices, their "Oxy-pre" variables are quantities that could proxy for high values of the demand parameter θ. Unlike Rx prices that can dampen the consumption effect of falling Im prices, the demand parameter magnifies them. See also the online appendix.

V. Extensions

The appendix shows similar sufficient-statistics results with income effects, income heterogeneity, and preference heterogeneity, which were

[31] Furr-Holden et al. (2021). However, adulteration may not be the entire explanation, because the race gap in elderly opioid deaths follows a similar pattern to the age-45+ series shown in fig. 4 even though there was no race gap among the elderly before 2013 in terms of nonopioid-drug deaths.

left out of the aggregate model featured in propositions 1–6. Even if utility maximization is relaxed to be nonsatiation, price changes still have the two basic aggregate effects: some consumers jumping from one part of the budget set to another and an ordinary substitution effect among those who do not jump. Another extension of equation (2) is to have separate accounting for consumption and deaths, with illicit consumption being more dangerous. Mulligan (2020) analyzes these cases.

A comprehensive state and local policy database would also help understand how the full prices of Rx and Im opioids vary geographically and over time. Federal policies regarding drug addiction treatment, such as whether health insurance plans must cover substance-abuse treatment as an essential health benefit and what tools are available to treatment programs, have also changed. It is also worth investigating whether treatment programs are related to the divergent paths for adults and minors shown in figure 3 or the race gap reversal shown in figure 4.

This paper treats the price of Im opioids as a parameter, perhaps linked to the state of technology or law enforcement policy. A worthwhile extension would investigate whether at least the timing and location of Im price changes are connected to the prior state of Rx-opioid markets.

Consequences of marginal Rx price changes are treated in propositions 5 and 6, which weigh the aggregate effect of consumers jumping from one part of the budget set to another against the opposite behavior of consumers who move along their demand curve as they continue to source their opioids from Rx. In contrast, the effect of Rx fixed costs on opioid consumption would be unambiguous, because fixed costs do not move Rx consumers along their demand curve. Mixed consumption would complicate the analysis because added Rx fixed costs may shift consumers from mixed to Im only, which in model (1) increases the marginal cost of opioids.

Although a rigorous definition of aggregate-level epidemic dynamics is beyond the scope of this paper, note that model (2) predicts that even a constant trend for the log of prices or the log of the demand parameter would result in a sudden surge in aggregate consumption as consumers switch from Rx to Im. The peak contribution of switching to consumption growth would be at peak density, thereby giving the appearance of an "epidemic" or "diffusion" even though consumers in my model are not interconnected.

VI. Conclusions

An individual-choice model predicts the opioid consumption effects of a range of policy and technological changes, including prescription regulation, technological progress in illicit manufacturing, law enforcement, overdose treatments, and the labor market opportunity costs of drug addiction, to the extent that such policies influence the full price of opioids.

Not only do diverse shocks fit into a uniform structure, but the model reveals close quantitative relationships among their effects. Proposition 1 is one such result, establishing an equivalence in direction and magnitude between the effects of a price change common to prescription and illicitly manufactured opioids (such as overdose treatments) on the composition of opioid consumption and the aggregate-consumption effect of changing either one of the prices by itself.

In theory, even the direction of policy effects can change over time. This is consistent with previous empirical findings that opioid mortality increased in an earlier era because opioid prescriptions were liberally dispensed yet increased again later because of restrictions on prescription supply. With its sufficient-statistics results (propositions 5 and 6), the model clarifies how the sign and magnitude of the price difference between prescription and illicit markets may be responsible for these changes. The model also shows how recent fentanyl deaths among whites would appear at least partially a consequence of prior prescription habits (proposition 6) at the same time their opioid consumption would be surpassed by that of blacks, who have little prescription history (proposition 4). Reversing the race mortality gap in this way requires a persistent race gap in prescription access while illicit-opioid prices fall generally. The paper presents death certificate data showing that, in fact, (i) the black-white gap in opioid fatality rates changed sign, (ii) fatality rates among children and youth diverged from adult rates, and (iii) the cross-area relationship between the opioid fatality rate and its composition changed sign.

This is also the first paper to comprehensively catalog the dozens of changes in federal opioid policy, identified in 19 years of the Federal Register and from Department of Justice press releases, that potentially influence prices and costs. The overall pattern revealed in table 2 is that policies subsidized and facilitated opioid prescriptions from the year 2000 until about 2010. Later prescription regulations were tightened, while the war on illegal drugs was relaxed.

Much more can be learned about opioid markets. A significant fraction, if not a majority, of opioid misuse is sourced from illicit markets where the accuracy and variety of price and quantity measures are especially deficient. Such data would be a big step forward toward quantifying the price effects of many of the policies recorded in table 2, or at least further confirming the important premise that illicit opioids became significantly cheaper than prescriptions. Better predictions would also be possible with estimates of short- and long-run supply elasticities and how they are different for heroin and fentanyl.

Finally, this paper's theoretical results are consistent with various types of monetary and nonmonetary costs of nonmedical opioid use, but together the costs must induce a nonconvex budget set. The enormous productivity growth in illicit-opioid manufacturing—fentanyl analogs have become quite cheap—supports the assumption of low prices at high quantities. However, if individuals are also facing costs that create sufficient diminishing returns, then behavior would deviate substantially from the predictions in this paper.

Data Availability

Data and code for replicating the tables, figures, and other quantitative results in this paper and its online appendix can be found in Mulligan (2024) in the Harvard Dataverse, https://doi.org/10.7910/DVN/CZZPYD.

Appendix

Additional Consumer-Theory Results

Budget-set properties.—The consumer's budget constraint is piecewise linear in the $[Q, z]$ plane, formed as the upper envelope of the three linear budget constraints (lemma 1). Assuming that $f_I > f_R \geq 0$, four configurations are possible, depending how p_R/p_I fits into the intervals $0 < Q_{10} < 1 < Q_{01} < \infty$, where Q_{xy} denotes the magnitude of the marginal rate of substitution in $Q(\cdot)$ evaluated at $q_R = x$ and $q_I = y$. The upper envelope is only one piece if $p_R/p_I < Q_{10}$ (fig. 1*A*). If income is great enough and $f_R > 0$, the upper envelope consists of two pieces (as in fig. 1*B*) if $p_R/p_I \geq Q_{01}$ or $Q_{10} < p_R/p_I \leq 1$. The mixed (Im-only) constraint is dominated by the other two in the former (latter) case. The remaining interval for p_R/p_I is where three pieces are possible when $f_R > 0$, with the mixed piece forming the upper envelope at the highest quantities because $C(1, p_R, p_I; 0, 0) < p_I < p_R$. When f_R is sufficiently close to zero, the only difference is that the interval $1 < p_R/p_I < Q_{01}$ cannot have three pieces, because the Im-only piece is dominated by mixed consumption. The three-piece case is also less likely when Rx and Im are close substitutes: a small gap between Q_{10} and Q_{01}. The case aggregating to equation (2) is $Q_{01} \leq p_R/p_I \wedge y > f_I p_R/(p_R - p_I) \wedge f_R = 0$. A second case would differ only in replacing p_I with $C(1, p_R, p_I; 0, 0)$.

Additional heterogeneity.—Let $\theta \in \Theta$ be a vector indexing consumer-preference characteristics; the main text presents the scalar special case. Average consumption (eq. [2]) is generalized as

$$\int_{\Theta}\int_0^{f^*(p_R,p_I;\theta)} M(p_I, y - f; \theta) g(f, \theta) df\, d\theta + \int_{\Theta}\int_{f^*(p_R,p_I;\theta)}^{\infty} M(p_R, y; \theta) g(f, \theta) df\, d\theta,$$

where M denotes the Marshallian demand corresponding to the indirect utility function v, now indexed by θ; $g(f, \theta)$ is the density function. As a vector, θ cannot be factored outside the equivalent variation $f^*(\cdot)$ as it is in the main text. With the following definitions, the effect of p_R on average consumption is still signed by equation (8); see the online appendix for details and proof steps:

$$\text{CROSSSR} \equiv p_{\text{R}} \frac{\int_{\Theta} (A(\theta)/\text{ARCSR}) \left(\partial \int_0^{f^*(p_{\text{R}}, p_{\text{I}}; \theta)} M(p_{\text{I}}, y - f; \theta) g(f, \theta) df / \partial p_{\text{R}} \right) d\theta}{\int_{\Theta} \int_0^{f^*(p_{\text{R}}, p_{\text{I}}; \theta)} M(p_{\text{I}}, y - f; \theta) g(f, \theta)\, df\, d\theta},$$

$$\text{ARCSR} \equiv \frac{\int_{\Theta} A(\theta) g(f^*(p_{\text{R}}, p_{\text{I}}; \theta), \theta)\, d\theta}{\int_{\Theta} g(f^*(p_{\text{R}}, p_{\text{I}}; \theta), \theta)\, d\theta},$$

where $A(\theta)$ denotes an individual-level Hicksian arc elasticity and ARCSR its aggregate among consumers indifferent between sources; POINTSR is defined as the consumption-weighted average Marshallian point elasticity among Rx consumers, and r still denotes the Rx quantity share.

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