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ABSTRACT

Marginal prices fell, and disposable incomes increased, for drug and alcohol consumers during the pandemic. Most of the amount, timing, and composition of the 240,000 deaths involving alcohol and drugs since early 2020 can be explained by income effects and category-specific price changes. For alcohol, the pandemic shifted consumption from bars and restaurants to homes, where marginal money prices are lower. For more dangerous illegal drugs like fentanyl and methamphetamine, the full price of consumption also significantly fell whenever employment became financially less attractive, as it was while unemployment bonuses were elevated. Both the wage effect and income effects further reduced marginal opioid prices by inducing shifts toward cheap fentanyl. Drug mortality dipped in the months between the \$600 and \$300 bonuses, especially for age groups participating most in UI. A corollary to this analysis is that national employment rates will be slow to recover due to the increased prevalence of alcohol and, especially, drug addiction.

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I. Introduction

After a series of innovations ranging from germ theory to cancer treatments increased human life expectancy, a century-long longevity trend stopped and began to reverse. By 2016, the U.S. had surpassed 100,000 deaths annually from alcohol- or drug-induced causes, with more than 90 percent of the deaths occurring among the nonelderly. The mortality rate from these causes jumped to even higher levels in 2020, where they appear to have remained at least through mid 2021. Behind the mortality statistics are millions who survived past consumption but will struggle with drug or alcohol addictions in the years ahead.

Did the unprecedented changes in regulatory and government spending policies have important effects on drug and alcohol mortality? This paper takes a first step toward an answer by partitioning mortality changes between shifts in consumer demand for drugs and alcohol and movements along a given demand function. Specifically, I document changes in disposable income, marginal money prices of drugs and alcohol, and the full price of (especially) drugs as it relates to the value of time. Each is a demand variable that would be expected to change behavior even without any change in preferences, and in fact has done so in the past. The paper investigates qualitative hypotheses generated by the fact that the various demand factors vary over time, across substances, and across demographic groups. In addition, it takes a calibration approach to assess the likely magnitude of these affects as they might have been estimated before the pandemic and compares the predictions to the 2020-21 data. No other public health framework offers such a rich array of quantitative predictions with one simple model.

The nationwide increase in disposable personal income in 2020 and 2021 was extraordinary and unprecedented due to the cash transfers distributed by the federal government. However, I assume that, in partially Ricardian fashion (Barro 1974), even individuals with significant mortality risk from substance abuse save a lot of the transfers. Moreover, I assume that their marginal propensity to consume the abused substances is no different than their propensity to purchase other available goods and services. This suggests that an income effect by itself is small, although not negligible (on the scale of historical changes in mortality) due to

the amount that personal income increased relative to the opportunities to make normal purchases. Even irrational consumers have a budget constraint, which pandemic-transfer policies relaxed in a way not experienced in previous recessions.

Substance abuse, especially drug use, has been related to low wages and employment (Case and Deaton 2020). Although directions of causality are debated (Currie, Jin and Schnell 2019), the household budget constraint suggests that two of them are opposite sides of the same coin. To the extent that drug use is complementary with nonwork, reducing the price of one encourages demand for the other. Unemployment benefits, as distinct from “stimulus checks,” affect the value of time, which is part of the full price of substance abuse to the degree that significant amounts of time are required to acquire, administer, and recover from substance use (Becker 1965). Ruhm (2019), Case and Deaton (2020), Currie and Schwandt (2020), and others conclude that unemployment in past recessions had fairly small short-run effects on drug and alcohol mortality. However, past changes in the value of time were of less magnitude and affecting a smaller fraction of the population than the large and historically unprecedented unemployment bonuses paid in 2020 and early 2021.¹ Most of the past recessions also occurred before 2014, when illicit fentanyl became easily accessible. Nor did the unemployed and others receive such generous cash transfers, or face reduced opportunities to spend, as they did in 2020-21. This paper shows how larger drug consumption changes in 2020-21 are consistent with the previous findings.

The value of time was not the only demand factor changing in 2020-21. Although its relevance is rarely noted in studies of drug and alcohol abuse, the money prices of opioid and alcohol consumption differ significantly among types or consumption venues. Public policy and other economic changes might unintentionally increase total drug and alcohol consumption by curtailing supply of high-priced sources and pushing consumers to “low quality” sources with low marginal prices. Indeed, this was already observed in opioid markets as early as 2010 when consumers switched to cheaper heroin, and later even cheaper fentanyl, when more expensive prescription opioids became less available (Alpert, Powell and Pacula 2018, Evans, Lieber and Power 2019, Mallatt 2018, Powell, Alpert and Pacula 2019, Ruhm 2019, Schnell 2018). My findings suggest that narcotics demand increases were amplified by this kind of segment

¹ The weekly unemployment bonus paid in 2009 was only \$25, as compared to the \$600 paid in 2020 to a much larger eligible population.

substitution in 2020-21 because the supply of relatively expensive segments such as heroin and prescription opioids expanded less readily than cheaper and more deadly fentanyl did. A contribution of this paper and a previous one (Mulligan 2020) is to provide a unified framework for quantifying segment-substitution effects during the various episodes.

For alcohol, beverages are cheaper when purchased at a liquor or grocery store for consumption off the store premises (“at home”). Consumers often prefer to drink at a bar or restaurant, but when prevented from doing so their total drinking may increase because it occurs where the alcohol is cheaper. One difference between alcohol-segment substitution and narcotics-segment substitution is that the former can occur entirely at the individual level. In contrast, the segment-substitution effect for narcotics is necessarily mediated through the market. Even individuals without any narcotic-demand shift could consume greater quantities and experience greater mortality during the pandemic because of the demand increases of others.

In many applications of consumer demand theory, substitution between quantity and quality (such as service, branding, or packaging) may be of little relevance because the marginal consumer is indifferent between the low- and high-priced segments. The indifference may also hold for drug and alcohol abuse, but mortality and health are not held even approximately constant in the substitution because they especially depend on quantity.

I find that, unlike suicide deaths, alcohol-induced deaths and deaths involving drug poisoning in the U.S. were each above prior trends. As before the pandemic, these deaths were primarily involving alcohol, narcotics, or crystal methamphetamine (meth) deaths. Never in the time frame for measuring these deaths (going back to 1999), has any of these three categories deviated so much from trend as they did in 2020 and 2021. As predicted by the calibrated demand model, the percentage and absolute deviations are greatest for narcotics, then for alcohol, and then for meth. Consistent with the value-of-time effect, narcotics and meth deaths return temporarily (almost) back to trend during the second half of 2020 when unemployment bonuses were temporarily suspended. The time series for drug mortality follows the time series for unemployment bonuses most closely for working age populations. Measured alcohol-induced deaths are also similar to the quantitative predictions from the demand model, which

come primarily from a segment-substitution effect.² For drug and alcohol mortality overall, the value-of-time effect of unemployment bonuses accounts for a significant fraction, although less than half, of the 2020-21 increase.

A rich literature, surveyed recently by Evans and Popova (2017), has considered whether government transfers encourage spending on “temptation goods” such as alcoholic beverages.³ Although temptation goods are normal goods, they conclude, and I agree, that transfer recipients spend the funds on much more than temptation goods. Evans and Popova further emphasize that many of the policies in their study encourage investment in work-related skills, which discourages drinking (and smoking) enough to offset the income effect. Presumably policies such as unemployment bonuses that discourage work would instead have substitution effects reinforcing the income effect.

Section II introduces the conceptual framework for projecting income effects, value-of-time effects, and segment-substitution effects based on pre-pandemic observations of drug and alcohol markets. Sections III and IV presents the drug and alcohol mortality data, respectively. These data also suggest that tens of millions of Americans have alcohol use disorder or illicit drug use disorder and that their numbers increased 8 million during 2020 and 2021. Section V tests the model’s distinct predictions for drug mortality by age due to differential exposure to unemployment benefits.

Throughout the paper, I follow the modern literature and refer to individuals with “substance use disorder,” a group that excludes those who legally use drugs or alcohol according to their doctor’s instructions. Substance abuse refers to the consumption of substances by those with substance use disorder. Among them are individuals with significant mortality risk from substance abuse and are of primary interest in a study of alcohol and drug mortality.

² Alcohol consumption usually leads to death with a longer time lag, although death better indicates the timing of consumption in acute cases, which are part of this paper’s analysis.

³ However, none of the studies in the survey looked at consumption of illegal drugs.

II. A Demand System for Alcohol and Drug Consumption

Three quantifiable demand factors changed substantially in 2020 and 2021: the marginal prices of drugs and alcohol, disposable income, and the value of time. Here I present an analytical framework that guides a quantitative assessment of each factor and shows how predictions differ across time, substances, and demographic groups. Sections III and IV follow with discussion of mortality data and pre-pandemic demand-parameter estimates.

II.A. Segment-Substitution Effects

This paper emphasizes that the marginal opportunity costs of alcohol and drug consumption are context specific. For alcohol, a key distinction is whether the alcohol is consumed at home, or away from home, where the financial cost of each ounce consumed is greater. For narcotics, which refer primarily to opioids but also cocaine and psychedelics, illicit fentanyl(s) has been an emerging product with significantly lower marginal cost and more elastic supply than the others. The pandemic and pandemic policies can change the consumption context directly, as with shutting down bars and restaurants, or indirectly by shifting demand against differentially elastic supplies.

Here I apply the analytical framework of Mulligan (2020) to obtain quantitative predictions as to how much segment-substitution effects would contribute to changes in mortality in 2020 and 2021. Let p_H and $p_L < p_H$ denote marginal prices in two mutually exclusive contexts. Let $\phi F(p_H, p_L)$ denote the fraction of the population that consumes in the low-price context, with the partial derivatives $F_1 > 0$ and $F_2 < 0$. $\phi > 0$ is a shifter to be used for comparative static analysis. Especially for alcohol, shifting consumption context from bars and restaurants to home ($d\phi > 0$) is a form of prevention during the pandemic. This prevention may be imposed by the state, as with stay-at-home and business-closure orders, but at least as often is voluntary (Goolsbee and Syverson 2021).

Conditional on context, consumption is $\mu M(p_L)$ and $\mu M(p_H)$, respectively, with $M' < 0$ reflecting the law of demand. $\mu > 0$ is a context-independent shifter for comparative static analysis, representing changes in consumer income or in the incentive to engage in substitute behaviors such as employment. Aggregate consumption Q is therefore (1):

$$Q = \phi F(p_H, p_L) \mu M(p_L) + [1 - \phi F(p_H, p_L)] \mu M(p_H) \quad (1)$$

Comparative statics can be calculated with respect to all four parameters ϕ , μ , p_H and p_L . For reasons to be shown in Section IV, the first comparative static is of particular interest for alcohol consumption:

$$\left. \frac{dQ}{d\phi} \right|_{dp_L=dp_H=0} = F(p_H, p_L) \mu [M(p_L) - M(p_H)] > 0 \quad (2)$$

In words, for each unit added to the fraction of consumers in the low-price context, $M(p_L) - M(p_H) > 0$ units are added to total consumption. One of the quantitative questions this paper attempts to answer is the degree to which prices differ between contexts.

Let s_L denote the share of consumption that occurs in the low-price context. Equation (3) is the same comparative static as (2) except expressed in logs and relative to the log change in consumption specific to the high-price context:

$$\left. \frac{\frac{d \ln Q}{d\phi}}{\frac{d}{d\phi} \ln \{ [1 - \phi F(p_H, p_L)] \mu M(p_H) \}} \right|_{dp_L=dp_H=0} = - \left[\frac{M(p_L)}{M(p_H)} - 1 \right] (1 - s_L) < 0 \quad (3)$$

$$s_L \equiv \frac{\phi F(p_H, p_L) M(p_L)}{\phi F(p_H, p_L) M(p_L) + [1 - \phi F(p_H, p_L)] M(p_H)} \quad (4)$$

The RHS of (3) depends on the share s_L , the prices in the two contexts, and the price sensitivity of context-specific demand. If each of these were measured before the pandemic, equation (3) could predict the increase in total consumption during the pandemic for each unit change in the log of high-price consumption induced by a change in ϕ .

A second result helps for assessing the point elasticities of context-specific demand, denoted $\eta_L < 0$ and $\eta_H < 0$. A change in the marginal prices p_L and p_H that leaves F constant induces a log quantity change that resembles the share-weighted average of the point elasticities, as shown in equation (5).

$$\left. \frac{dQ}{Q} \right|_{d\phi=0=dF(p_H, p_L)} = s_L \eta_L \frac{dp_L}{p_L} + (1 - s_L) \eta_H \frac{dp_H}{p_H} \quad (5)$$

Several studies of alcohol and drug consumption have estimated the effects of excise taxes changes and other price changes that are fairly common across contexts (Gallet 2007, Gallet 2014). To the extent that such changes induce little change in ϕF and that the point elasticities are similar across contexts, they provide information about magnitudes of η_L and η_H .

The pandemic itself did not necessarily curtail the supply of a more expensive drug segment as it did for alcohol.⁴ However, unlike alcohol for home, bar, or restaurant consumption, or fentanyl in the case of narcotics, the expensive narcotics segment is not elastically supplied in the short run. Heroin, which is more expensive than fentanyl, is derived from the poppy plant, which requires agricultural land that goes unnoticed by law enforcement. Prescription opioids are also more expensive and require a doctor's prescription, which law enforcement has closely monitored in recent years. Therefore, changes in market-level narcotics demand μ increase the price p_H in the high-price narcotics segment, which can raise total consumption by encouraging switches to cheaper fentanyl. A simple third result illustrates this by varying both the demand parameter μ and price p_H to keep constant total consumption in the high-price segment.⁵ Equation (6) calculates the share of the total quantity change that results from segment switching as opposed to movement along each of the demand curves:

$$\left. \frac{d \ln Q - s_L d \ln \mu}{d \ln Q} \right|_{d[1-\phi F(p_H, p_L)]\mu M(p_H)=0=dp_L} = \frac{1}{1 + \frac{s_L}{1-s_L} \frac{M(p_H)}{M(p_L)} - \frac{\eta_H}{CROSS}} \quad (6)$$

$$CROSS \equiv \frac{p_H}{F(p_H, p_L)} \frac{\partial F(p_H, p_L)}{\partial p_H} > 0 \quad (7)$$

The RHS of equation (6) depends on the same terms as in equation (3), plus value of CROSS, which is the cross-price elasticity of low-price segment demand with respect to p_H . The segment switching share can range from zero (as CROSS approaches zero) to an upper bound less than 100 percent of the total quantity change.

⁴ Even before the pandemic, narcotics tended to be consumed privately.

⁵ A fixed supply to the high-priced segment would result in exactly such an equilibrium increase in p_H with μ . Appendix II considers results with more elastic supply.

II.B. Income Effects

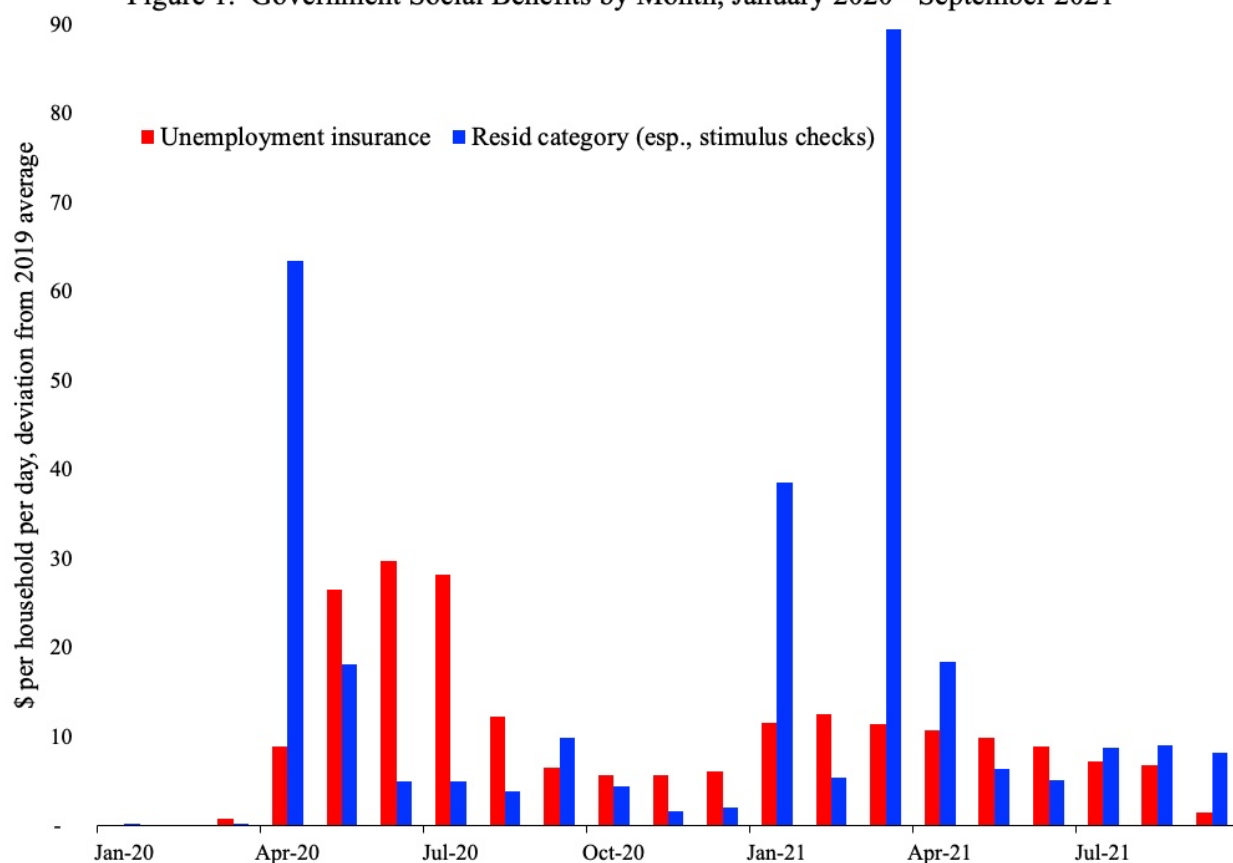
The results above can be used to model income and wage effects.⁶ For substances with both segments elastically supplied (esp., alcohol), income and wage effects by themselves would not change the composition of consumption between the two segments. Consumption of each would increase in proportion to μ . In cases (esp., narcotics) where supply is differentially elastic between the two segments, a comparative static such as equation (6) is relevant. My purpose here is to assess the possible magnitude of income effects on substance abuse during 2020 and 2021, which is needed for quantitative analysis in either case.

Figure 1 displays two categories of government social benefits, primarily cash, that were amplified during the pandemic. The amounts are shown as dollars per household per day. The red bars are unemployment benefits, which were elevated for two reasons. One was the increase in the number of persons eligible due to historic job loss as well as statutory loosening of eligibility criteria. Job loss was prolonged for months, while the looser criteria persisted until September 2021. The second factor contributing to the red bars was unemployment bonuses, paid primarily in May through July 2020 and again in January through August 2021.⁷ The weekly bonuses were \$600 during the earlier period and \$300 during the latter.

⁶ Income effects on consumption are driven largely by the consumer's budget constraint rather than their "rationality" (Becker 1962).

⁷ Twenty-six states ended the bonuses earlier, beginning in June.

Figure 1. Government Social Benefits by Month, January 2020 - September 2021



The blue series is “other government social benefits,” which during this period were primarily the “stimulus checks,” otherwise known as “Economic Impact Payments.” The checks were paid in three rounds. The first round in April and early May 2020 consisted of \$1200 payments per adult and lesser amounts for children. The second round was paid in the first half of January 2021 as \$600 per person. The third round was \$1400 per person received especially in the last full week of March 2021 (Waggoner 2021). The cumulative income shown in Figure 1 is \$6,452 of unemployment benefits and \$9,303 of other benefits over the 19 pandemic months shown.⁸ Together they amount to about 10 percent of median disposable income and a larger percentage of incomes below the median.

Although not reflected in the personal income accounting, the rent-moratorium policy launched with the March 2020 CARES Act is also potentially important. As long as it lasted (17 months), tenants could defer their monthly rent payments. I let τ denote the fraction of the

⁸ Although it was a recession, cumulative real disposable personal income per household increased almost \$12,000 (2020 dollars).

population of interest that is a tenant, as opposed to living in owner-occupied housing, institutional housing, or being homeless. Among them, the pre-pandemic budget share for rent is r . Let g denote the amount of the aforementioned cash transfers as a share of disposable income.

One potential reaction to all three of these programs could be for consumers to save all of the assistance. Indeed, the aggregate personal savings rate surged well beyond previous records when households received the transfers. However, at least for the sake of argument, I consider the possibility that individuals with significant mortality risk from substance abuse have a lower propensity to save beyond the 19 months than the general population does (Petty 2001). In other words, they have a greater marginal propensity $m > 0$ to consume the assistance before the programs end. The population's proportional increase in consumer spending other than rent is therefore $(1+gm)/(1-rm)$ for tenants and $(1+gm)$ for the others.

The marginal propensity to consume $m < 1$ by itself tends to make consumption increase in a lesser percentage than income does (g). On the other hand, reduced spending on rent and potentially other items means that spending on abused substances might increase in a greater percentage than income does even if the income elasticity of the demand for those substance is no greater than one. Using $g = 0.10$ (cited above), $\tau = 0.27$ (Centers for Disease Control and Prevention 2021), and an average rent budget share of $r = 0.233$ (OECD 2021), the proportional increase in consumption resulting from the income effects of the three relief policies is close to linear in m . At $m = 1/2$, the increase is about 8.5 percent.⁹

II.C. Wage Effects

Unemployment bonuses, the rent moratorium, and the stimulus checks have important economic differences. As part of the unemployment system, the bonuses are targeted toward those who were employed in the months before the pandemic, which is disproportionately those of working age. The bonuses are paid contingent on not returning to work and thereby have a substitution effect associated with the value of time, which varied over time during 2020 and

⁹ The percentage increase in consumption ranges from zero at $m = 0$ and 19 percent at $m = 1$. See Parrott and Zandi (2021) for more information about the rent moratorium and the degree of tenant participation.

2021 due to historic statutory changes in unemployment benefits. As a substitution effect, the qualitative prediction is that substance abuse would be greater during weeks when unemployment benefits were more generous regardless of the consumers propensity to save.

This wage effect would be greatest among working-age people because they are especially like to be eligible for unemployment benefits. However, especially for narcotics consumption, unemployment insurance (UI) benefit policy still affects consumption of those not receiving unemployment benefits because they participate in markets where others are receiving unemployment benefits. Recall that the market-level substitution effect is the focus of equation (6).

In order to offer quantitative predictions for the wage effect, I use Becker's (1965) household production framework with three uses of time: leisure time, work time, and time spent taking, acquiring, and recovering from substance use (hereafter, "substance use time"). The consumer receives a wage w for time worked (n) and an unemployment benefit b for time not worked ($1-n$), including the time involving substance use.¹⁰ Consumer demand is described by a utility function defined over three goods:

$$\max_{n,Q} u(nw + (1-n)b - pQ, 1-n-\theta Q, Q) \quad (8)$$

where p is the marginal money price of the abused substance. The constant $\theta > 0$ is the time required for each unit of substance consumed, which presumably varies across substances. The first argument in the utility function is consumption other than the abused substance, whose price is normalized to one. For interior solutions, the first-order conditions for utility-maximizing labor supply and substance abuse together imply (9):

$$\frac{u_3}{u_1} = p + (w - b)\theta \quad (9)$$

where the u subscripts denote the function's partial derivatives and the ratio is the marginal rate of substitution between the abused substance and all other goods. The condition (9) reveals that the full price of substance abuse is the money price plus the value of the required time. For consumers at an interior solution, unemployment benefits reduce the value time because they

¹⁰ Time can be interpreted in units of weeks, which is the interval at which unemployment benefits are administered.

reduce the net proceeds from “selling time” to an employer (that is, spending time working). The $b\theta$ term indicates how policy changes would have differential effects across substances and demographic groups, with increases in the benefit rate b reducing the full price at rate θ .

The quantitative result (9) is independent of the magnitude of the effect of b on work time n as long as the first-order conditions remain interior.¹¹ To put it another way, unemployment or nonemployment is not synonymous with a low value of time, even without unemployment benefits. Some individuals are out of work because of few market opportunities. Others are out of work despite market opportunities because they have high reservation wages. Even if the former is more common than the latter, nonemployment is an imperfect proxy for the value of time, which (in this model) is the variable in the substance-demand function. The large and time varying unemployment bonuses are, from a research perspective, a unique episode for measuring large changes in the value of time.

II.D. Short- and long-run demand

The available demand parameter estimates (Sections III and IV) are long-run estimates, at least from the perspective of a weekly or monthly time frame. Especially with habit- and tolerance-forming substances such as drugs and alcohol, consumers might respond to an unanticipated permanent increase in income or full-price reduction by progressively increasing consumption until they reach a new higher steady-state level of consumption. I use a distributed-lag approach to model the distinction between short and long run. Specifically, even a one-time change in price or income has a prolonged effect on consumption and deaths Q , as modeled by equation (10):

¹¹ An alternative approach would be to assume that substance abuse affects only the productivity of time at work, in which case the full price of the abused substance would depend on b only indirectly through n . I leave this approach to future research, noting here that substance abuse affects nonwork activities too. Time is required to obtain the substance, especially if it is illegal one, and to push through withdrawal symptoms. Time may be spent in a hospital recovering from nonfatal overdose, or in a rehab facility. Absenteeism is a frequently-noted indicator of substance abuse (Frone 2013). Descriptions of drug addiction sometimes note how “getting the drug, using it, and recovering from it can consume [the user]” (American Addiction Centers 2021).

$$\ln Q_t = \lambda \ln Q_{t-1} + (1 - \lambda)D(y_t, p_t, w_t - b_t) \quad (10)$$

where t denotes time and $D(y, p, w - b)$ long-run demand (in logs) as a function of income, money prices, and the value of time, respectively. The constant $\lambda \in (0, 1)$ is the “lag parameter.” Solving (10) forward from the beginning of the pandemic ($t = 0$),

$$\ln Q_t = \lambda^t \ln Q_0 + (1 - \lambda) \sum_{s=0}^{t-1} \lambda^s D(y_{t-s}, p_{t-s}, w_{t-s} - b_{t-s}) \quad (11)$$

Equation (12)’s summation term is implemented with weekly time series on the demand factors. The predicted quantities are aggregated to monthly in order to match the mortality data (Sections III and IV). My primary specification uses a weekly lag parameter of $\lambda = 3/4$, with sensitivity analysis shown in Appendix II.

As revealed in Figure 1, the \$600 weekly bonus period was shorter-lived than the \$300 bonus. Because of the lag structure (13), the peak demand impact of the \$600 is, in theory, therefore somewhat less than double the peak demand impact of the \$300.

II.E. Summary of Predictions

In summary, the 2020 and 2021 consumption of each of alcohol, narcotics, and meth are predicted to be above prior trends by at least the income effect of the stimulus checks, rent moratorium, and unemployment bonuses, which I estimate to be about 8.5 percent. In addition, the consumption of narcotics and meth, especially in the working-age population, should rise and fall according to the timing of unemployment benefits. Based on equation (6) and explained further below, the narcotics increase and fluctuations should be more amplified than those for meth, with magnitudes consistent with segment-substitution patterns before 2020. Perhaps surprisingly, the relatively high-priced narcotics segments should not increase, and may even decrease, at the same time that fentanyl increases substantially.

Alcohol consumption should also increase more than the income effect, with a time pattern reflecting the time pattern of the share of consumption occurring at home that determines the average marginal price of alcohol consumption. The magnitude of the additional alcohol increase is dictated by the price-elasticity of alcohol demand, which is observable from historical data, and the amount that marginal prices fell. Because this additional alcohol increase derives from the consumption side rather than time allocation, it should be similar for working-age and non-working-age groups. Its timing would also be different from the timing of unemployment bonuses and stimulus checks to the extent that their timing differs from the timing of consumer mobility.

The timing of changes in deaths involving substance abuse may differ from the magnitude of changes in the consumption of the substances, especially for alcohol that often leads to death through chronic conditions rather than acute poisoning, which is common with illicit drugs. As noted below, timing is partly addressed by looking at acute alcohol deaths as well as the larger category of deaths from alcohol-induced causes.

The substance consumption and mortality may not remain in fixed proportions, which means that the percentage increase in deaths differs from the percentage increase in consumption. One approach is to reinterpret $M(p_L)$ and $M(p_H)$ in terms of mortality rather than consumption (see also Mulligan 2020). Alcohol consumption might not be greater at home than at bars or restaurants, but home consumption be more dangerous due to different amounts of supervision at the various locations. A related argument has been made for fentanyl consumption versus consumption of other opioids. In each of these cases, quantitative conclusions for mortality might be more reliably obtained from mortality elasticities (this paper's approach) than from consumption elasticities.¹²

¹² Over a period of time when fentanyl deaths increased by an order of magnitude, Mulligan (2021) shows that crime-lab reports of fentanyl quantities and death rates involving fentanyl closely (and proportionally) track each other.

III. Data on Drug Fatalities and Drug-demand Parameters

III.A. Mortality sources and trends

Fatalities are measured using the on-line CDC-Wonder tools, sponsored by the Centers for Disease Control and Prevention (CDC), for tabulating every death certificate filed with a U.S. state or District of Columbia (essentially every death in the country). The death certificates are provided to CDC by the states on a rolling basis, with the timing and quality of initial submissions varying across states. CDC also takes time to process and code them, especially the 20 percent of certificates that CDC does not receive digitally. As a result, CDC sponsors two distinct tools: “Multiple Cause of Death, 1999-2020” and “Provisional Mortality Statistics, 2018 through Last Month.” The data accessed with the Provisional tool is still being processed and coded, especially the most recent six months and for “external causes of death” such as drug overdose.¹³ Given that I accessed the tools in late December 2021 and early January 2022, the series shown in this paper end in June 2021.

Each death certificate “contains a single underlying cause of death, up to twenty additional multiple causes, and demographic data” such as age (Centers for Disease Control and Prevention 2022). The tools permit tabulation by any of the thousands of underlying causes, or by selected cause groups such as “Alcohol-induced causes”, “Drug-induced causes,” “Drug/Alcohol Induced Causes,” or “Suicide.” Death certificates can also be tabulated by any of the thousands of additional (and more specific) multiple causes, such as unintentional heroin poisoning. Because the demand analysis relates first to consumption, I select drug-involved deaths using the multiple causes.¹⁴ The narcotics causes are ICD-10 T codes 40.0/opium, 40.1/heroin, 40.2/other opioids, 40.3/methadone, 40.4/synthetic narcotics, T40.5/cocaine, T40.6/unspecified narcotics, T40.7/cannabis, T40.8/lysergide[LSD], and T40.9/unspecified

¹³ For every month of 2020, each of my series could be obtained from either tool. I used “Multiple Cause of Death, 1999-2020” and note that differences from the Provisional tool are nonzero but negligible.

¹⁴ In practice, 94 percent of the 2020 death certificates with at least one type of narcotic or psychotropic poisoning listed among the multiple causes also have drug-induced cause cited as the single (group of) underlying cause.

psychodysleptics [hallucinogens].¹⁵ T40.4 is primarily fentanyl and its analogs, which I refer to as fentanyl(s). Almost all of the opioid T codes appearing in the data that are not fentanyl are either heroin (T40.1) or prescription opioids (T40.2). Many death certificates contain multiple narcotics codes and the CDC-Wonder tools allow tabulating the intersections necessary to avoid double-counting when aggregating across codes.¹⁶ I refer to the psychotropics codes (T43.0 through T43.9) as “meth” because 81 percent of 2020 death certificates citing those codes cite the T43.6 code and therefore likely crystal methamphetamine.

Beginning in 2020, the death certificates potentially include a code (U07.1) for COVID-19 among the causes of death. The counts of death certificates including U07.1 are well known as they were extensively reported in the news as U.S. “COVID deaths.” However, minimal overlap occurs between the COVID death certificates and death certificates citing drug poisoning or alcohol-induced causes. Among all of the death certificates citing narcotics poisoning (T40) or meth poisoning (T43), only 0.1 percent cite COVID-19 as the underlying cause of death. Among all of the death certificates citing drug- or alcohol-induced causes as the underlying cause of death, less than one percent cite COVID-19 among any of the multiple causes. Because COVID-19 prevalence was typically less than one percent at any point in time in 2020 and 2021, these minimal overlaps are consistent with the hypothesis that drug and alcohol decedents are a random sample of the population with respect to COVID infection status.

Figure 2 displays the monthly time series for deaths involving narcotics (blue) and meth (black), expressed at annual rates by dividing monthly deaths by the number of days in the month and then multiplying by 365.25. Each solid line is the data from CDC Wonder. Deaths involving narcotics, deaths involving meth, and alcohol-induced deaths are all elevated in 2020 and 2021 to a degree that had not previously occurred over such a short period of time. Each

¹⁵ Although autopsies are generally uncommon, they occur in about 80 percent of drug deaths. The autopsy rates are even greater for the non-elderly and for deaths that occur outside a medical facility.

¹⁶ For the purposes of estimating consumption, it may be desirable to count a single death certificate multiple times, once for each recorded substance.

substance is associated with tens of thousands of additional deaths during those years. At the same time, there is no increase in suicides.¹⁷

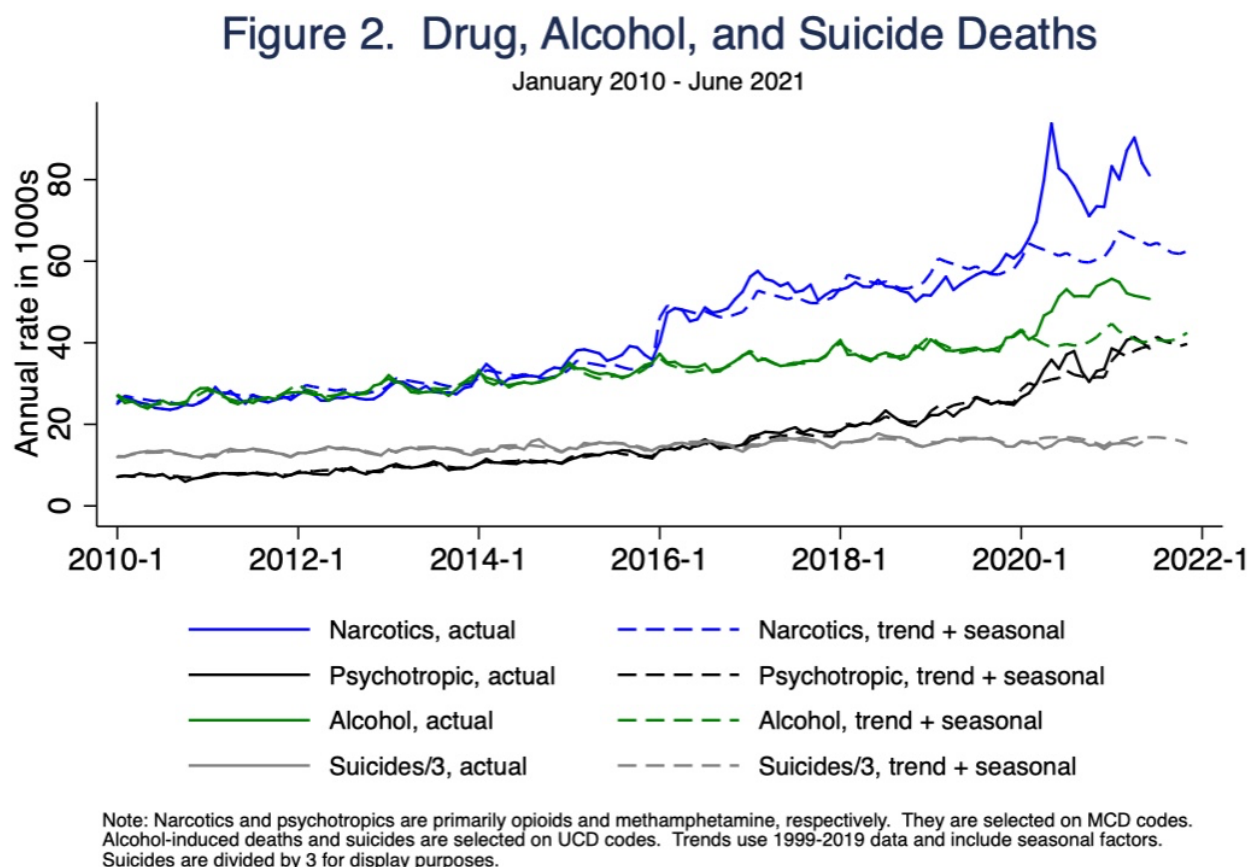


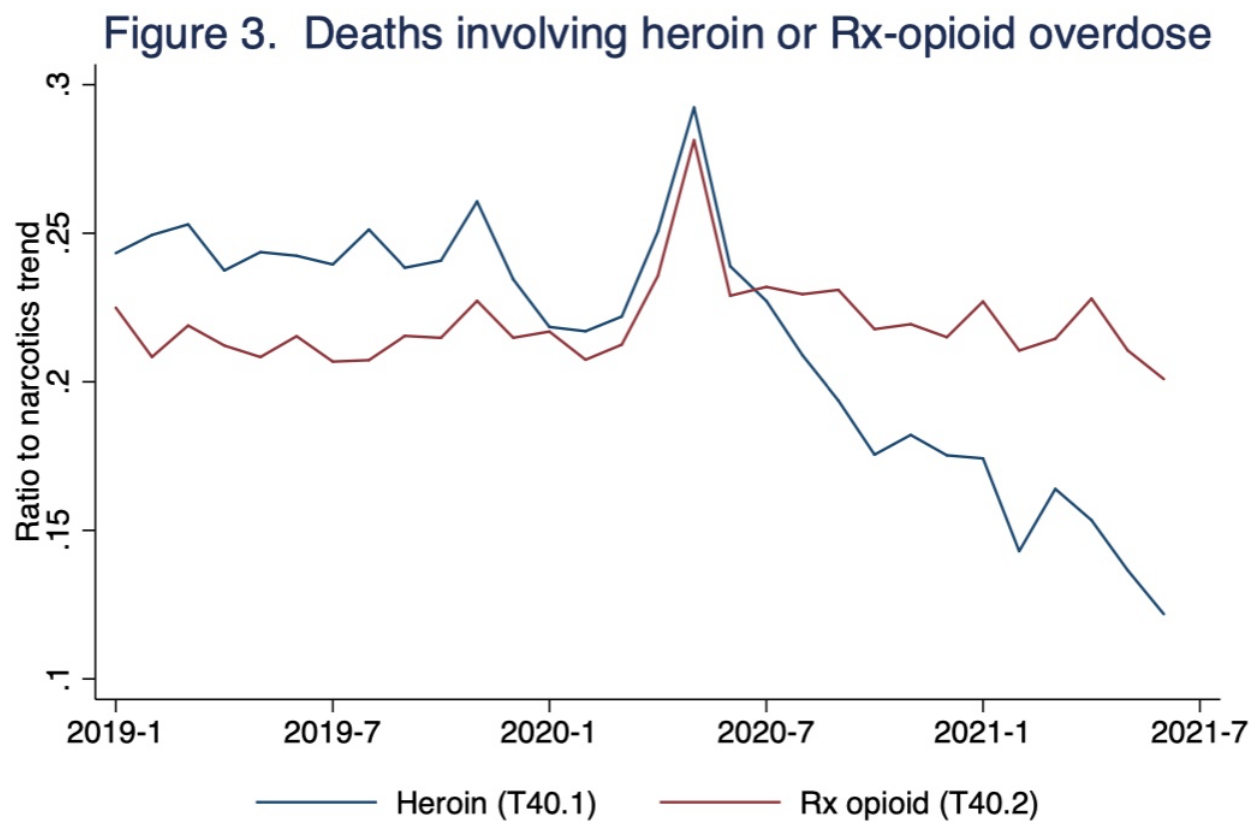
Figure 2’s dashed lines are “trends + seasonals” fitted to the pre-2020 data in logs, with a time quartic and indicators for month-of-year as explanatory variables. The narcotics equation also includes indicator variables for $\text{year} \geq 2006$ and $\text{year} \geq 2016$ due to the discrete increase in supply from Medicare Part D and from fentanyl at those times, respectively (Council of Economic Advisers April 2019). With meth in an exponential growth phase for several years through 2019, largely because of rapid productivity growth achieved by small-scale illicit meth producers, it is perhaps unsurprising that meth mortality would grow rapidly too in 2020 and 2021.¹⁸ More surprising, and relevant from some of the analysis that follows, is that much of the increase in meth fatalities occurs from December to January rather than from month to month

¹⁷ See also Ridout, et al. (2021), who note increased anxiety during the pandemic but little change from 2019 in suicide-related emergency department visits.

¹⁸ Rapid technological progress has increasingly enabled large-scale, potent meth production by criminals with little more than high-school chemistry training. The population mortality rate from meth grew exponentially since about 2008, averaging 30 percent annually through 2019.

during the rest of the year. Deaths that are alcohol induced or involving narcotics also follow a seasonal, with alcohol deaths elevated in the winter months and narcotics elevated early in the calendar year. Appendix I shows the regression equations used to calculate the dashed lines.

At least qualitatively consistent with the theory, the narcotics series exceeds its own trend more in 2020 and 2021 than meth does, as shown by the blue and black series in Figure 2. Nevertheless, heroin and prescription opioids fail to keep up with the trend for the narcotics category, as shown in Figure 3. Heroin and prescription opioids are elevated in May 2020 and perhaps April, even though heroin falls significantly during the remainder of the pandemic and Rx opioids fail to increase. Perhaps the switch to fentanyl took a few weeks on the demand or supply sides.



Note: Trend predictions for combined narcotics deaths use data through 1999-2019 and include a monthly seasonal factor.

III.B. Calibration

In addition to the income effect already estimated at about 8.5 percent, six other parameters must be quantified in order to obtain quantitative predictions for either narcotics or

meth consumption. Equation (6)’s segment-substitution effect (on total category consumption) requires a share parameter, a cross-segment price elasticity, an own-price elasticity for the category, and the relative price of the two segments.¹⁹ I assume this effect occurs at a constant rate throughout the period, which multiplies the income effect cited above and the wage effect that follows. Equation (9)’s wage effect requires an estimate of θ , the time required for each unit of substance consumed, which I treat as a constant over time for each substance. It also requires estimates of the change in unemployment benefits, which I take as the time series of the unemployment bonuses multiplied by a constant estimate of the share of potential substance abusers who would be eligible for the bonuses.

Table 1 shows how I calibrate the parameters for narcotics and alcohol (see also Section IV). Because I have mortality data rather than consumption data, ideally the price elasticities would be deaths with respect to price rather than consumption with respect to price. Soni (2018) has one such estimate (−0.49) based on the rollout of prescription-opioid subsidies delivered through Medicare Part D in 2006. Mulligan (2020) finds an elasticity of deaths involving illicitly-manufacturer opioids with respect to the price of prescription opioids of about 2 based on changes in prescription manufacturing beginning in 2010. Acknowledging the inherent challenges of measuring prices of illicitly-manufactured opioids, Mulligan (2020) estimates a price ratio of 3.0 between prescriptions and illicitly-manufactured opioids.²⁰ The Multiple Cause of Death data show 2019 deaths involving fentanyl (T40.4) to be about 60 percent of deaths involving narcotics generally.²¹ From equation (6), these four parameters imply that 47 percent of any increase in log overall narcotics consumption that derives from a segment-neutral increase in demand ($d\mu > 0$) would be the amplification effect of segment substitution. In other words, the change in log overall narcotics consumption is about twice ($1/(1-0.47)$) as large as it would be if the segment share F were held fixed.

¹⁹ Equation (6) specifies both an arc elasticity and a point elasticity, which I treat as equal for calibration purposes.

²⁰ The natural log of 3 (1.1) is entered in Table 1.

²¹ The 0.6 share includes “double-counted” deaths (i.e., death certificates listing more than one narcotic) in both the numerator and denominator.

Table 1. Calibration of Long-run Substitution Effects on Total Category Consumption

Substitution effect and parameter	Narcotics	Alcohol	Sources
<i>Segment-substitution effect</i>			
Category own-price elasticity	-0.49	-0.85	Narcotics: Soni (2018) from rollout of Medicare Part D. Alcohol: from Finland and Russia price cuts.
Segment cross-price elasticity	2	N/A	Mulligan (2020)
Segment log price differential	1.10	1.10	Narcotics: Mulligan (2020). Alcohol: Schulfer (2019), Gordon (2013)
Low-segment share			
Pre-pandemic level	0.6	0.18	CDC Wonder; Consumer Expenditure Survey (New Strategist 2015)
Change in 2020-21	N/A	Series	Google mobility time series scaled to bartender employment series
Share of log quantity change that is segment substitution	0.47	N/A	Derived using Equation (6)
<i>Wage effect</i>			
Time requirements			
Substance use	0.17	0	Share of time endowment based on Florence, Luo and Rice (2021)
Other consumption goods	0.09	0	Assumed between 0 and substance use
Share of users with recent work history	0.57	N/A	2019 NSDUH
Unemployment benefit change	Time series		UI bonuses (\$600, \$300, or \$0) weekly through June 2021
Full price effect of \$300 UI bonus			
as a share of the money price	-0.24	0	Money price of narcotics assumed to be \$15 per day of use.
on log deaths involving the substance	0.12	0	Derived from the previous row, own-price elasticity, work history share, and segment-substitution amplifier (top panel).

Notes: Price elasticity sources measure deaths with respect to money prices. Segment-substitution effects are assumed zero for meth. Meth wage effect is assumed to be the same as narcotics.

Studies of the productivity of substance abuse typically note the problem of absenteeism, presumed to be related to the time to acquire, administer and recover from the substance use. Florence, Luo and Rice (2021) estimate a 17 percent productivity loss for opioid users, which I take as a 17 percent loss of a day's time endowment for each day of use, as modeled in equation (8). According to equation (9), increasing the unemployment bonus by \$300 per week (\$43 per day) would reduce the full price of narcotics consumption by \$7.29 per day. A \$600 bonus would reduce the full price by \$14.57 per day, which could be enough to offset the entire money price. That is, such a bonus could induce about same consumption and mortality as a zero money price would. Demand at zero money price is presumably high, although still finite which means that it would be improper, in this range, to assume a constant elasticity of consumption or mortality with respect to the money price. In order to derive a point estimate for the wage effect, I therefore assume linear demand for money prices below p_L with local elasticity equal to the elasticity shown in the first row of Table 1.

Because equation (9) exaggerates the relative full price effect by ignoring any time requirements for other consumption, I consider it as an upper bound on the full price effect of b . The lower bound is 0 as long as substance abuse is no less time intensive per unit expenditure than other consumption is. Without a point estimate of the time requirements for ordinary consumption, I take the midpoint of the upper and lower bounds for the purposes of preparing Table 1. Sensitivity analysis is presented in Appendix II.

Traditionally unemployment benefits were paid only to individuals who were looking for work *and* had a recent work history. Substance abusers or persons near the margin of substance abuse, but without a work history, therefore would not have their substance demand shifted by the unemployment bonuses.²² I use the 2019 National Survey on Drug Use and Health (NSDUH) to estimate the employment rate for persons over age 14 reporting nonmedical consumption of either prescription opioids or heroin. This rate (0.57) appears in Table 1's narcotics column. Accounting for time requirements for other consumption, a \$300 bonus

²² They likely would not receive the bonuses. Indeed, U.S. Department of Labor (2021) data show that only two percent of elderly persons – who often do not have recent work histories – received unemployment benefits in June 2020 as compared to almost ten percent at middle age. Even if a consumer received bonuses without a recent work history, equation (9) would not apply if their optimal labor supply is a corner solution.

therefore reduces the relative full price by an amount equal to 24 percent of the money price,²³ but only for 57 percent of the potential consumers, which is an average price cut of 14 percent of the money price. As consumers in both segments increase their demand in response to a lower full price, this induces a shift toward the more elastically supplied fentanyl, which further reduces marginal prices for those who shift (equation (6) and the top panel of Table 1). The combined substitution effects of a \$300 unemployment bonus policy are projected to increase log narcotics mortality by 0.12 and meth mortality by 0.07.²⁴ Putting aside for the moment that these are long run substitution effects, applying this increase to the trend deaths of 63,000 annually involving narcotics and 34,000 involving meth, that is 10,700 additional narcotics and meth deaths for each year that a \$300 bonus is in place.

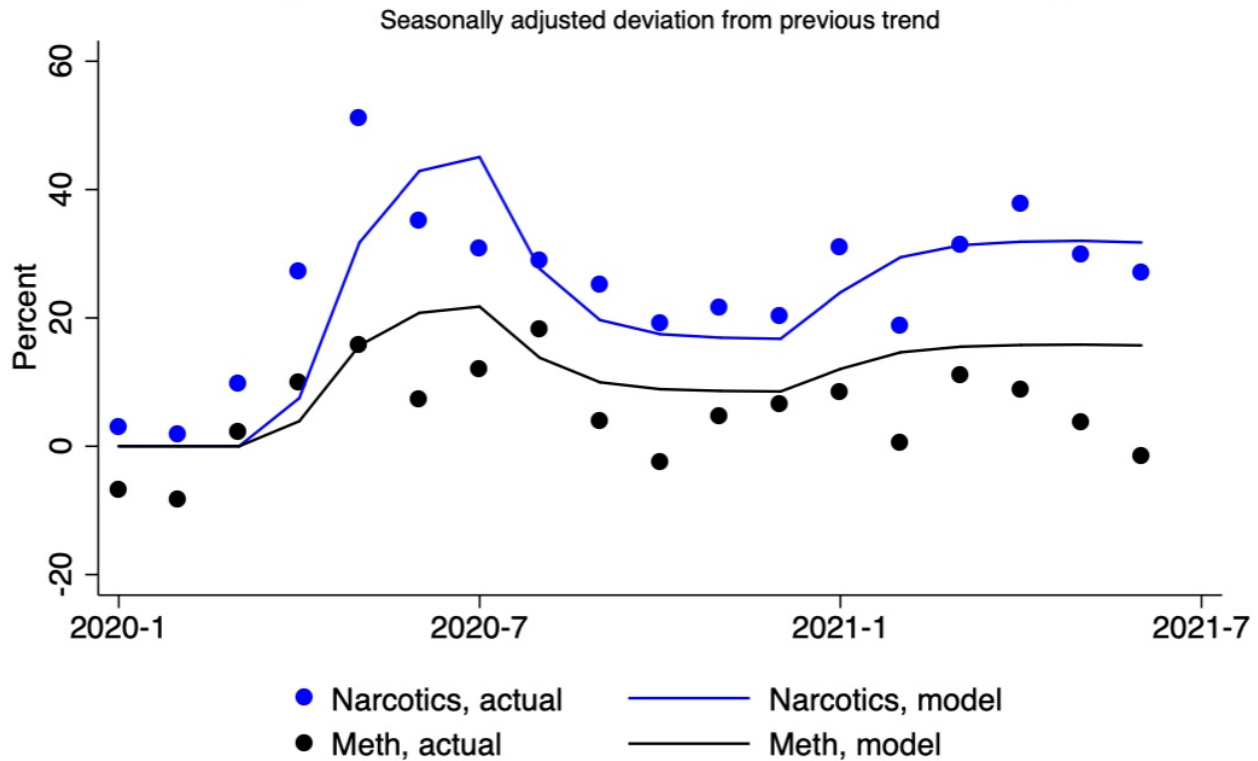
III.C. Data and model compared

Figure 4 compares the mortality data with the demand model's predictions, separately for narcotics and meth. The nontrivial demand factors in the model are the income effect and wage effect, which are the same for the two substances except that narcotics demand is amplified by segment substitution. Note that Figure 4's predictions do not use any information beyond 2019, except for the amounts and timing of the unemployment bonuses, rent moratorium and stimulus checks. Because the 8.5 percent income effect is essentially constant beginning in April 2020 (see Appendix II), the predictions vary over time due to the wage effects. Especially, the unemployment bonus was zero in August through December 2020. As an amplifier, the segment substitution effect for narcotics is the reason why the model predicts greater narcotics increases above trend than for meth. It is also the reason why narcotics predictions vary more over time.

²³ Noting the difficulty of measuring the denominator of the 0.24 ratio due to illicit markets and variability across consumers, I assume a denominator of \$15 per day of use as described in Quinones (2015).

²⁴ Narcotics mortality increases in a greater proportion due to induced shifts to cheaper fentanyl.

Figure 4. Deaths involving drug poisoning



Note: Trends and seasonals are estimated from data 1999-2019. Actual mortality is from CDC Wonder.

Both model and data show historically large increases above trend, with each tick in Figure 4 equal to twenty percentage points. As predicted, both narcotics and meth mortality data are greater in the spring of 2020 than in the second half of the year. Also as predicted, narcotics mortality is elevated again in the first half of 2021 and somewhat less than in May-June 2020 because the 2021 unemployment bonus amount was halved. The meth data do not so clearly confirm elevated mortality in early 2021, although the model itself shows that the predicted increase is small on the overall scale of Figure 4.

For the full pandemic months having available death-certificate data (April 2020 through June 2021), Table 2's top and middle panels correspond to Figures 2 and 4, respectively, as well as showing the sum across substances. The middle panel also includes a row corresponding to the demand model without income effect, which for narcotics and meth is the wage effect of unemployment bonus, including induced segment-substitution effects. The model suggests that the substitution effects of the unemployment bonuses alone resulted in about 8,400 deaths involving narcotics poisoning and 2,300 deaths involving meth poisoning through June 2021.

Table 2. Substance Use and Fatalities: Model and Data

April 2020 - June 2021

	Narcotics	Meth	Alcohol	Total
<i>Number of deaths</i>				
Trend & seasonals	78,481	42,497	50,998	171,976
Full model	99,810	48,275	62,150	210,235
Actual	101,217	45,417	64,813	211,447
<i>Deaths above trend and seasonal</i>				
Trend & seasonals	0	0	0	0
Model without income effect	8,403	2,333	7,257	17,992
Full model	21,329	5,778	11,152	38,259
Actual	22,735	2,920	13,815	39,471
<i>Alive with substance use disorder, 1000s</i>				
Trend & seasonals	10,374	12,783	15,664	38,821
Actual	13,379	13,662	19,907	46,948
Actual deviation from trend	3,005	878	4,243	8,127
<i>Years of life lost, 1000s</i>				
Trend & seasonals	2,940	1,599	1,341	5,880
Actual	3,813	1,711	1,741	7,265
Actual deviation from trend	873	112	399	1,385

Notes: The substance-abuse population is assumed to be 165, 376, and 384 (narcotics, meth, and alcohol, respectively) per annual death based on data from before 2020 as detailed in Appendix I. COVID life-years lost (not shown) are 7.0 million. The total column is a simple sum, and therefore counts twice the 24 percent of death certificates with narcotics or meth that cite both. However, the table excludes death certificates citing "unspecified" drug poisonings without citing narcotics or meth, which number about half of the dual narcotics-meth certificates. Only 0.2 percent of the alcohol deaths also cite narcotics or meth.

The third panel uses the death statistics to impute numbers of individuals with substance use disorder, as defined in the National Surveys on Drug Use and Health (NSDUH), based on the substance-specific ratios these two occurred before 2020. As explained further in Appendix III, I attempt to adjust for NSDUH's well-known undercount of illicit drug use based on Barocas et

al.'s (2018) multisample stratified capture-recapture approach. Tens of millions appear to have substance use disorder, 8 million of which is an increase above the pre-pandemic trend.

The final panel shows estimates of years of life lost from these fatalities. They are estimated by taking the mortality data in gender-age-substance cells and applying 2019 remaining-life tables at the gender-age level published by the Social Security Administration (Social Security Administration 2021). About 7 million life years were lost to alcohol- and drug-induced deaths, which is similar to the 7 million life years lost to deaths caused by COVID-19 during the same time period. The alcohol and drug deviation from trend is about 1.4 million life years.²⁵

My conclusion that drug consumption was increased by wage and income effects in 2020-21 does not contradict the observation that unemployment in previous recessions had little effect on drug consumption. Adjusted for inflation, the weekly unemployment bonus in 2009 was about \$30, although the unemployed were also potentially eligible for mortgage assistance.²⁶ Even if the all-in 2009 bonus were \$60 per week, that is either 10 or 20 percent of the 2020 and 2021 bonuses, respectively. Momentarily putting aside amplification of income and wage effects through segment-substitution, the 2009 change in log drug mortality predicted from my Table 1 wage effect would only be 0.01 rather than 0.07 for a \$300 bonus. The 2009 drop in real disposable personal income – a first in 35 years – could easily have resulted in a combined wage and income effect that reduced drug and alcohol consumption, rather than increasing it.

²⁵ Table 2's total column is a simple sum, and therefore counts twice the 24 percent of death certificates with narcotics or meth that cite both. However, Table 2 excludes death certificates that cite poisoning from "unspecified" drugs without also citing narcotics or meth, which number about half the number of dual narcotics-meth certificates. See also Ruhm (2018). Only 0.2 percent of the alcohol deaths also cite narcotics or meth.

²⁶ Health insurance assistance for the unemployed was also expanded in both 2009 (Mulligan 2012) and 2020.

IV. Data on Alcohol Prices and Fatalities

IV.A. Alcohol Fatalities

I used the aforementioned CDC-Wonder tools to tabulate death certificates indicating an underlying cause of death that is among the “Alcohol-induced causes,” which are “the subset of alcohol-related deaths that are certain to be caused by drinking alcohol” (Spillane, et al. 2020). Specifically, the alcohol-induced causes shown in my Figure 2 and Table 2 are alcohol-induced pseudo-Cushing syndrome (T-code E24.4), mental and behavioral disorders due to alcohol use (F10), degeneration of nervous system due to alcohol (G31.2), alcoholic polyneuropathy (G62.1), alcoholic myopathy (G72.1), alcoholic cardiomyopathy (I42.6), alcoholic gastritis (K29.2), alcoholic liver disease (K70), alcohol-induced acute pancreatitis (K85.2), alcohol-induced chronic pancreatitis (K86.0), finding of alcohol in blood (R78.0), and alcohol poisoning (X45, X65, and Y15). Alcohol-induced causes do not include fatal drunk-driving accidents and other deaths where alcohol might have combined with other causes.

Trends and seasonals for the alcohol series are estimated using the same regression specification as for narcotics and meth. Alcohol mortality has a significant seasonal, with elevated mortality rates in the winter months. As shown by Table 2 and the green series in Figure 2, the annual rate of alcohol mortality after March 2020 was 14,000 (27 percent) above the previous trend.

Most of the alcohol-induced deaths cite alcoholic liver disease (K70), which is a chronic condition. Many of these deaths ultimately occurred in hospital, where life-extending medical treatments further adds to the time interval between death and final alcohol consumption. In order to better assess the timing of extraordinary alcohol consumption during the pandemic, I also used the CDC wonder tool to examine deaths that likely occurred close in time to final alcohol consumption: deaths occurring at home having underlying cause F10 or alcohol poisonings regardless of place of death. I also look at motor-vehicle traffic fatalities generally

(underlying cause codes selected from V01-V89) as well as those involving alcohol (multiple cause codes F10, R78.0, T51, X45, X65, or Y15).²⁷

IV.B. Alcohol Prices

It is well known that alcoholic beverages are more expensive in bars and restaurants than they are when purchased at a liquor or grocery store for consumption off the store premises. Such a price differential is also unsurprising because the former drinks come bundled with various services. Schulfer (2019) and Gordon (2013) estimate ratios of retail bar or restaurant prices to liquor-store prices that range from 2.7 to 3.6. In the calibration exercise that follows, this full range is used, with 3.0 as a preferred point estimate.²⁸

The Consumer Expenditure Survey tracks alcoholic-beverage expenditure separately according to consumption at home versus away from home. The away-from-home share was 0.39 in 2019 and slightly above 0.41 in earlier years; I use 0.40.²⁹ At the 3.0 relative price, that puts the away quantity share at 0.18.

Figure 5 shows bartender employment during 2020 and 2021, which is measured in the Current Population Survey (CPS) during one week each month. During the pandemic it averaged about 40 percent below what it was in February 2020. Its largest dips were in April 2020 and at the end of 2020.³⁰ In order to have a weekly series that could be aggregated to represent entire months (as the fatalities data do) rather than merely CPS survey weeks, I regressed survey-week bartender employment on Google mobility measures for the same survey weeks.³¹ The regression's fitted values for all weeks are shown in Figure 5.

²⁷ CDC-Wonder's "Motor Vehicle Traffic" category excludes codes among V01-V89 that are specifically designated as "nontraffic."

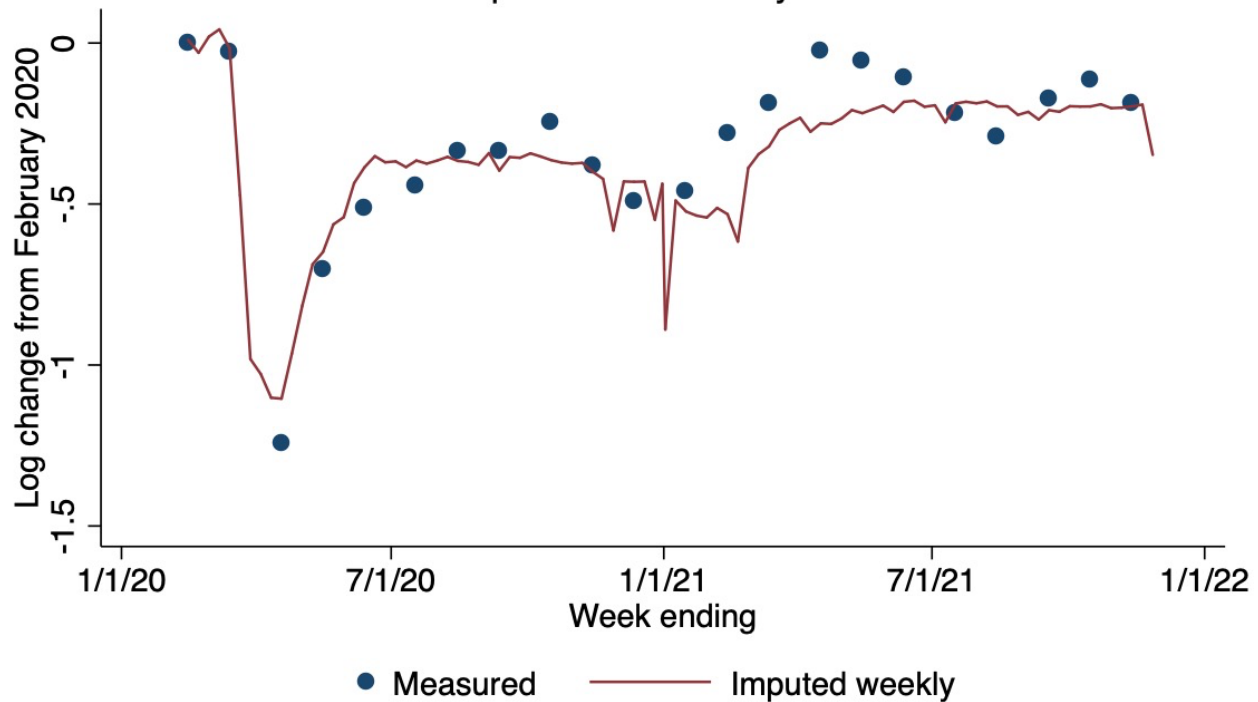
²⁸ The point estimate's natural log is shown in the Alcohol column of Table 1.

²⁹ Conway (2021) and New Strategist (2015).

³⁰ The shift of alcohol consumption from bars and restaurants did not seem to reduce deaths from auto accidents involving alcohol, which were greater during the pandemic by about the same proportion as auto accidents generally.

³¹ Google (2021) describes the two mobility regressors as "retail and recreation" and "workplaces."

Figure 5. Bartender employment dynamics
imputed from mobility data



Notes: Bartender employment is from the CPS survey week. Imputations are fitted values from a regression on retail and work mobility, measured weekly.

In order to transform Figure 5's weekly bartender series into a long-run price effect for use in equation (14), I calibrate equation (3)'s three parameters. The calibration is shown in Table 1's Alcohol column. A large literature offers estimates of the price elasticity of demand for alcoholic beverages.³² A number of other studies link prices directly to alcohol deaths, which is the outcome of interest in this paper. For example, alcohol prices fell about 22 percent in Finland when Estonia joined the European Union in 2004 thereby removing trade barriers between the two countries and encouraging Finland to reduce its excise tax (Koski, et al. 2007). Herttua, Makela and Martikainen (2008) estimate that alcohol-related mortality in Finland increased about 23.5 percent by 2005.³³ Inflation-adjusted vodka prices fell 77 percent in Russian between 1990 and 1994 when fatal alcohol poisonings increased by a factor of 3.5.³⁴ Although the data is less reliable, a similar quantitative relationship between vodka prices and

³² Many of them report elasticities of about -1 , although often they are for specific segments and provide little information about cross-price effects, which are presumably positive (Saffer and Chaloupka 1994).

³³ Koski, et al. (2007) found a 17 percent increase already by end of 2004.

³⁴ Nemstov (2002). Hospitalizations with alcohol psychoses increased by a factor of 3.8.

fatal alcohol poisonings in Russia is observed during Gorbachev’s earlier anti-alcohol campaign (Nemtsov 2002, Treisman 2010). Both the Finnish and Yeltsin price-reduction episodes imply the same arc elasticity up to two decimal places, which is the -0.85 entry shown in Table 1.³⁵ Applying Table 1’s three calibrated parameters to equation (3), I rescale Figure 5’s weekly log bartender series by a factor of -0.28 to obtain a weekly price effect series.

The value of time effect on alcohol use is likely much smaller than, and perhaps in a different direction from, the effect on drug use. “High-functioning alcoholics” are well known (Brody 2009). In contrast with illicit drug use, correlations between alcoholism and work absences are difficult to find (Frone 2013). My demand model therefore has zero value-of-time effect on alcohol mortality.

IV.C. Data and model compared

Figure 6 compares the mortality data (dots) with the demand model’s predictions (line). Because deaths from alcohol-induced causes can sometimes lag the decedent’s final consumption, which the model is constructed to describe, data are shown for both all alcohol-induced causes (solid dots) and alcohol-induced acute causes (hollow dots). The acute causes are about a quarter of the total. The remaining three-quarters are overwhelmingly deaths at in-patient medical facilities (hospitals), most of which are deaths from liver disease. Not surprisingly, the acute deaths reach near their peak two or three month before the overall series does.

It might seem that a sudden large jump in alcohol consumption would take years to show up in the mortality that is dominated by deaths from chronic conditions. However, 15 million people already suffered from alcohol-use disorder as measured by NSDUH. Even according to previous trends, more than 120,000 of them were expected to die from alcohol-induced causes in the next three years, primarily from liver disease. A consumption jump would accelerate their deaths, while adding to the stock of patients suffering from alcohol-related chronic conditions.

³⁵ For Finland, the arc elasticity calculation is $\ln(1+0.235)/\ln(1-0.22)$. For Yeltsin, it is $\ln(3.5)/\ln(1-0.77)$.

The additional 13,815 deaths shown in Table 2 is significant compared to prior trends but a small fraction of those with alcohol-use disorder.

The model predicts that deaths from alcohol-induced causes would be twenty to thirty percent above trend by April and remain there for almost a year until consumers largely returned to bars and restaurants. The data show the mortality increasing somewhat above thirty percent in the summer of 2020. Both model and data show a partial decline after an initial peak. The data do not obviously indicate the second peak predicted by the model on the basis of the second trough observed in the mobility and bartender series (recall Figure 5).

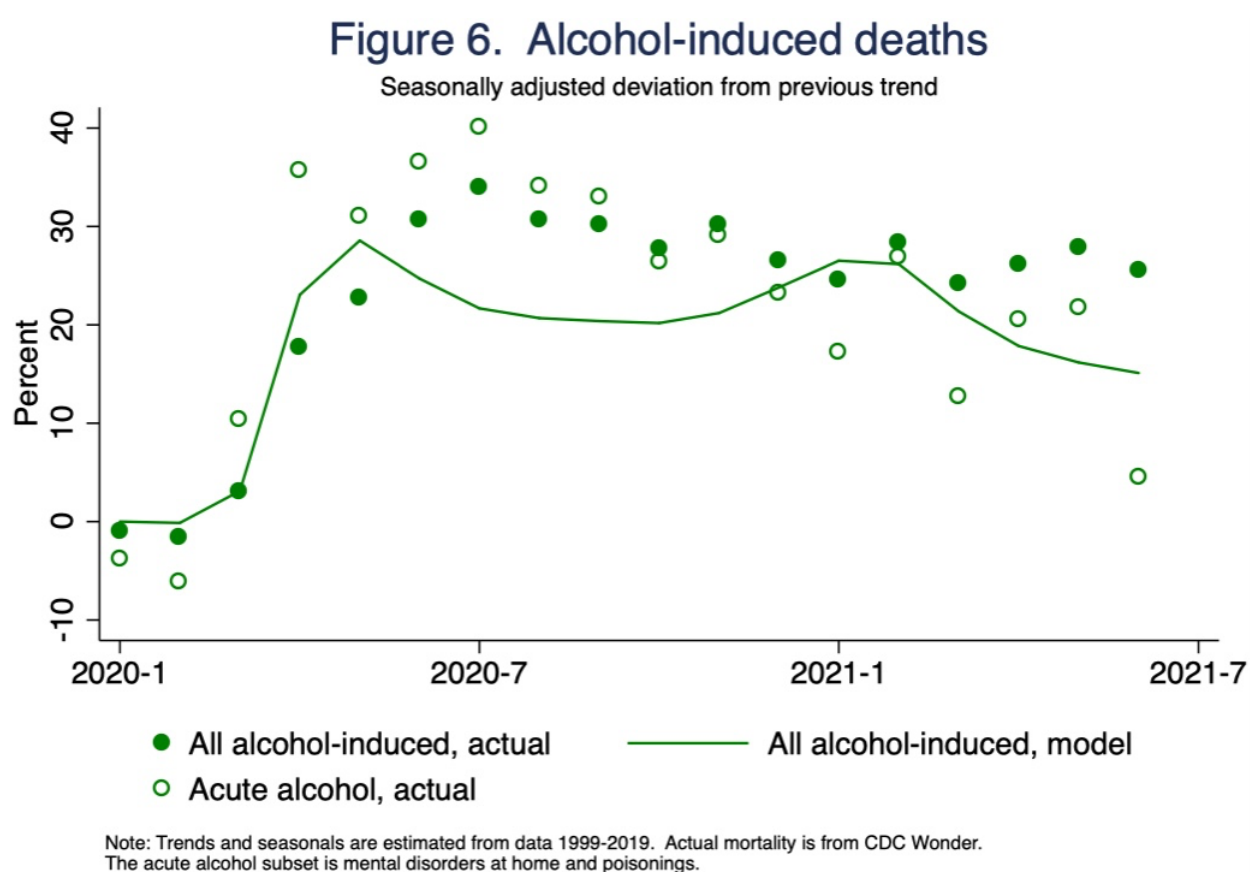
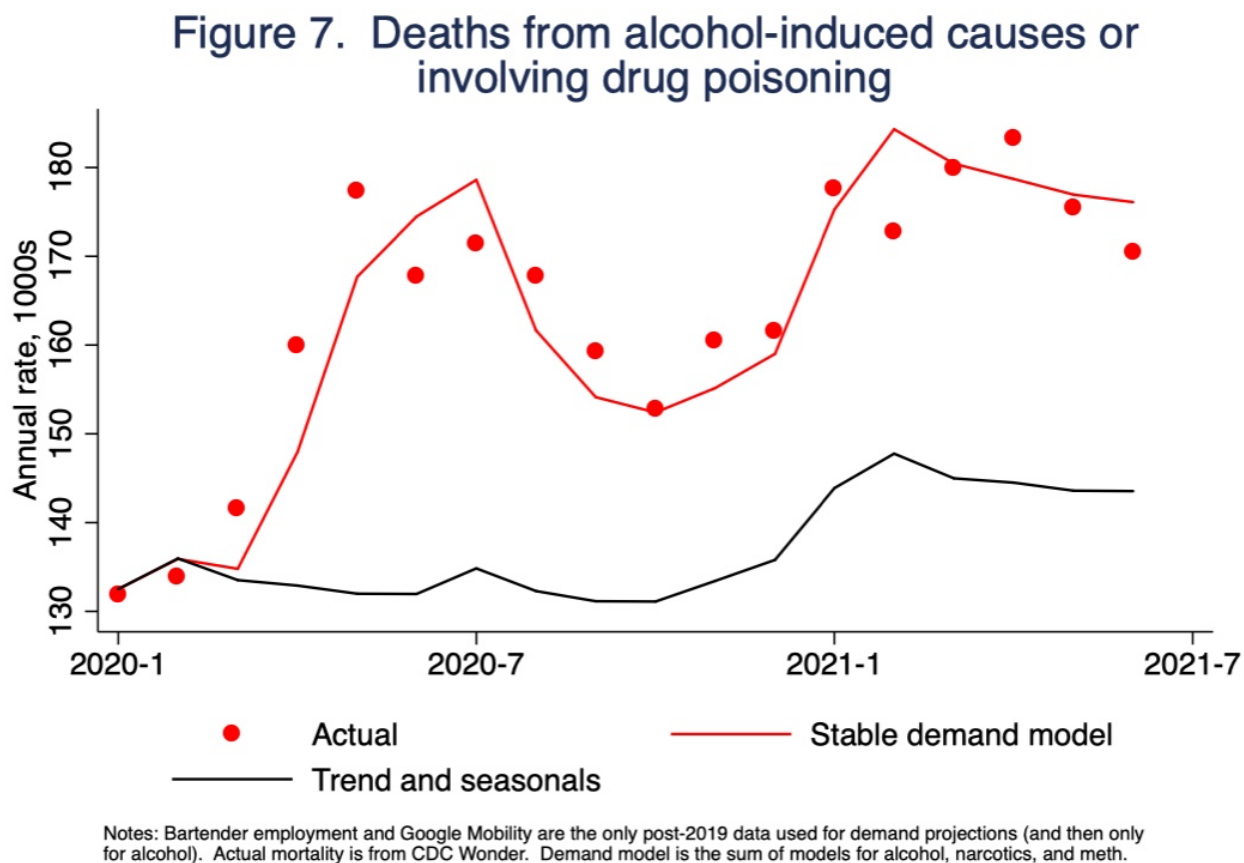


Figure 7 shows the model and data for the sum of alcohol-induced deaths, deaths involving narcotics, and deaths involving meth. The lower series shows the sum of the substance-specific trends and seasonals predicted based on the data from 1999 through 2019. The upper series adds on the demand model's aforementioned substance-specific income and substitution effects. The model predicts three turning points. The mortality data also show three

turning points of similar magnitudes to what is predicted by the model. However, the first and third turns occur at somewhat different times than the model predicts.



V. Alcohol and Drug Fatalities by Age

The demand model predicts three turning points for drug mortality between April 2020 and June 2021 largely because unemployment benefit policy occurred in three phases. The model also has distinct predictions by age due to differential exposure to employment and unemployment. This section investigates age patterns with a reduced form econometric model that would also be relevant for other causal interpretations of alcohol and drug mortality.

V.A. Monthly econometric models of alcohol and drug mortality

Unemployment benefits affect an individual's mortality in two ways. One is by shifting that individual's substance demand through income or wage effects. In theory, both shifts can occur even during weeks that he or she is employed, but only to the extent that (i) unemployment benefits are anticipated for periods of time out of work and (ii) are near the margin between working and not working (recall equation (9)). Workers in their 20s and 30s are especially likely to satisfy (i) and (ii), while youth and retired persons least likely.

The second effect occurs through the market. An individual who would have consumed prescriptions or heroin may be induced to switch to the more available fentanyl due to the effect of unemployment benefits on the demand of others. Unemployment benefits may therefore be expected to, among other things, significantly increase drug mortality among youth and retired persons although to a lesser degree than they increase drug mortality among persons of working age. I therefore begin with the aggregate monthly time series specifications that can capture the full equilibrium effect of unemployment bonuses. The aggregate specifications are of the form:

$$\ln Q_t = \beta_0 + \beta_1 UI_t + \beta_2 P_t + \beta_3 E_t + \beta_4 E_{t-1} + f(t) + m_t + \varepsilon_t \quad (15)$$

where Q is mortality expressed at an annual rate measured from January 1999 through June 2021. The β s are regression coefficients, which are restricted to zero as selected and noted in the regression tables. UI is the average weekly amount of the unemployment bonus, which is \$300 for April 2020 (\$600 for half the month and \$0 for the other half), \$600 for May through June 2020, \$300 for January through June 2021, and 0 for all other months before June 2021. P_t is a pandemic indicator, which is 1 for April 2020 through June 2021, $\frac{1}{2}$ for March 2020, and 0 for all other months before. E is the national employment-population ratio for the month. $f(t)$ is a function of time, specifically a quartic in time, and indicator for Medicare Part D (all months

beginning January 2006) and an indicator for fentanyl supply (all months beginning January 2016).³⁶ m is a vector of indicators for month of year (“seasonals”).

The reduced form econometric model is a bit different from the demand model used in Sections III and IV. The latter is specified at the substance-by-week level, has a lag structure (16), and makes predictions relative to trend and seasonals. The first column of Table 3 is therefore estimated with the demand-theoretical time series shown as the top series in Figure 7 over the time interval January 2020 through June 2021. The coefficient on the UI bonus variable is 0.052, which is less than the 0.12 shown at the bottom of Table 1 because meth and alcohol mortality are (in theory) less UI-sensitive than narcotics and because some of the UI effects continue even when they are set to zero in August 2020. In theory, the pandemic coefficient of 0.17 reflects income effects on all three substances as well as some of the UI effects that last beyond the period that \$600 bonuses were paid.

Table 3’s second column includes the corresponding specification estimated with the actual mortality data, but using the full period January 1999 through June 2021 and including the time quartic, seasonals, the Medicare indicator, and the fentanyl indicator. The estimated pandemic coefficient of 0.18 is similar to the theoretical prediction of 0.17, both of which are unprecedented in the U.S. series as a mortality increase over such a short time period. The estimated UI-bonus coefficient is economically and statistically significant, but somewhat less than the theoretical prediction. The next two columns show that adding the employment-population ratio to the regression hardly affects the result, but that the UI bonus coefficient is difficult to distinguish from the lagged employment-to-population ratio.³⁷

³⁶ The narcotics, meth, and alcohol death time series are fairly smooth, except large jumps up in January 2006 and January 2016 for narcotics only. This likely reflects the creation of Medicare Part D, which ultimately financed the majority of prescription-opioid purchases, and the introduction of illicit fentanyl to many regions of the U.S. (Council of Economic Advisers April 2019).

³⁷ In the first half of 2020, the employment series changes lead the bonus changes by about a month.

Table 3. Econometric models of alcohol and drug mortality, 1999-Jan through 2021-Jun
Cochrane-Orcutt AR(1) regressions, with dependent variable: log (alcohol+narcotics+meth deaths, annual rate)

Regressor	Theory	Monthly time series data			Month-by-age panel data			
UI bonus/300 (national)	0.052 (0.012)	0.033 (0.011)	0.035 (0.011)	0.022 (0.011)	0.027 (0.013)			
UI bonus/300 scaled by age-specific participation						0.39 (0.17)	0.37 (0.18)	0.24 (0.19)
Pandemic indicator (national)	0.17 (0.03)	0.18 (0.03)	0.19 (0.05)	0.17 (0.03)	0.21 (0.05)	0.21 (0.05)	0.19 (0.07)	0.21 (0.05)
Employment-to-population ratio (national)			0.19 (0.39)				-0.20 (0.54)	
Lagged employment-to-population ratio				-0.72 (0.29)				-0.75 (0.38)
Medicare indicator (post 2005)	N/A	0.036 (0.022)	0.035 (0.023)	0.043 (0.023)	0.027 (0.032)	0.027 (0.032)	0.028 (0.032)	0.031 (0.032)
Fentanyl indicator (post 2015)	N/A	0.082 (0.022)	0.084 (0.022)	0.079 (0.022)	0.079 (0.032)	0.079 (0.032)	0.079 (0.032)	0.078 (0.032)
Month-of-year indicators	N/A	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time quartic	N/A	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age indicators	N/A	No	No	No	Yes	Yes	Yes	Yes
Durbin-Watson stat (transformed)	N/A	2.3	2.3	2.4	2.7	2.7	2.7	2.7
Std. error of the regression	0.035	0.025	0.025	0.024	0.089	0.089	0.089	0.088
Observations	18	269	269	268	2,152	2,152	2,152	2,144

Notes: The theory column reports an OLS regression of the demand-theory's mortality impact (Figure 7) on UI and pandemic indicators. Each data column is a different specification, estimated in STATA using the corc option of the prais command. Age-specific UI participation is measured for June 2020. The pandemic indicator is 0 or 1, except for March 2020 when it is 0.5. Age groups are 0-21, 22-24, 25-34, 35-44, 45-54, 55-59, 60-64, 65+. Coefficient standard errors are in parentheses.

Table 4 repeats the theory-data comparison by substance, although aggregating meth and narcotics because the theory predicts that both of them are affected by UI. The theory predicts, and the point estimates confirm, that the UI bonus coefficient is greater and the pandemic coefficient less, for drugs than for alcohol.³⁸ The hypotheses of a zero UI coefficient or a zero pandemic coefficient in the drug-data regression can be rejected with 95 percent confidence. Neither of the hypotheses of a UI coefficient equal to 0.068 (the theoretical prediction) or a pandemic coefficient equal to 0.15 can be rejected.

Table 4. Theory and econometric mortality models compared
 OLS regression (theory, 2020-Jan through 2021-Jun) or
 Cochrane-Orcutt AR(1) regression (data, 1999-Jan through 2021-Jun)

Regressor	log(alcohol+drugs)		log(drugs)		log(alcohol)	
	Theory	Data	Theory	Data	Theory	Data
UI bonus/300 (national)	0.052 (0.011)	0.033 (0.011)	0.068 (0.018)	0.036 (0.018)	0.016 (0.010)	0.005 (0.010)
Pandemic indicator (national)	0.17 (0.03)	0.18 (0.03)	0.15 (0.06)	0.16 (0.06)	0.20 (0.02)	0.24 (0.02)
Medicare indicator (post 2005)	N/A	0.036 (0.022)	N/A	0.062 (0.039)	N/A	0.006 (0.012)
Fentanyl indicator (post 2015)	N/A	0.082 (0.022)	N/A	0.106 (0.039)	N/A	0.012 (0.012)
Month-of-year indicators	N/A	Yes	N/A	Yes	N/A	Yes
Time quartic	N/A	Yes	N/A	Yes	N/A	Yes
Std. error of the regression	0.035	0.025	0.050	0.041	0.032	0.025
Observations	18	269	18	269	18	269

Notes: The theoretical series are from Figure 7, Figure 6, or the difference between the two. All mortality is monthly, expressed at an annual rate. Coefficient standard errors are in parentheses.

The final four columns of Table 3 use month-by-age data. The first of these four show the regression corresponding to the table's first single-time-series specification, except adding indicator variables for each of the eight age groups, defined as the U.S. Department of Labor does for the purposes of tabulating the demographics of UI recipients. The remaining three columns replace the national UI variable with the product of the national variable and age-specific UI-claim rates for June 2020. In June 2020, the lowest ratios of UI claimants to

³⁸ Unsurprisingly, the Medicare and fentanyl coefficients are also greater for deaths involving drugs than for alcohol-induced deaths.

population were for the age 65+ group (0.0203) and the 16-21 age group (0.0469).³⁹ The greatest ratios were age 22-24 (0.1169) and 25-34 (0.1043).

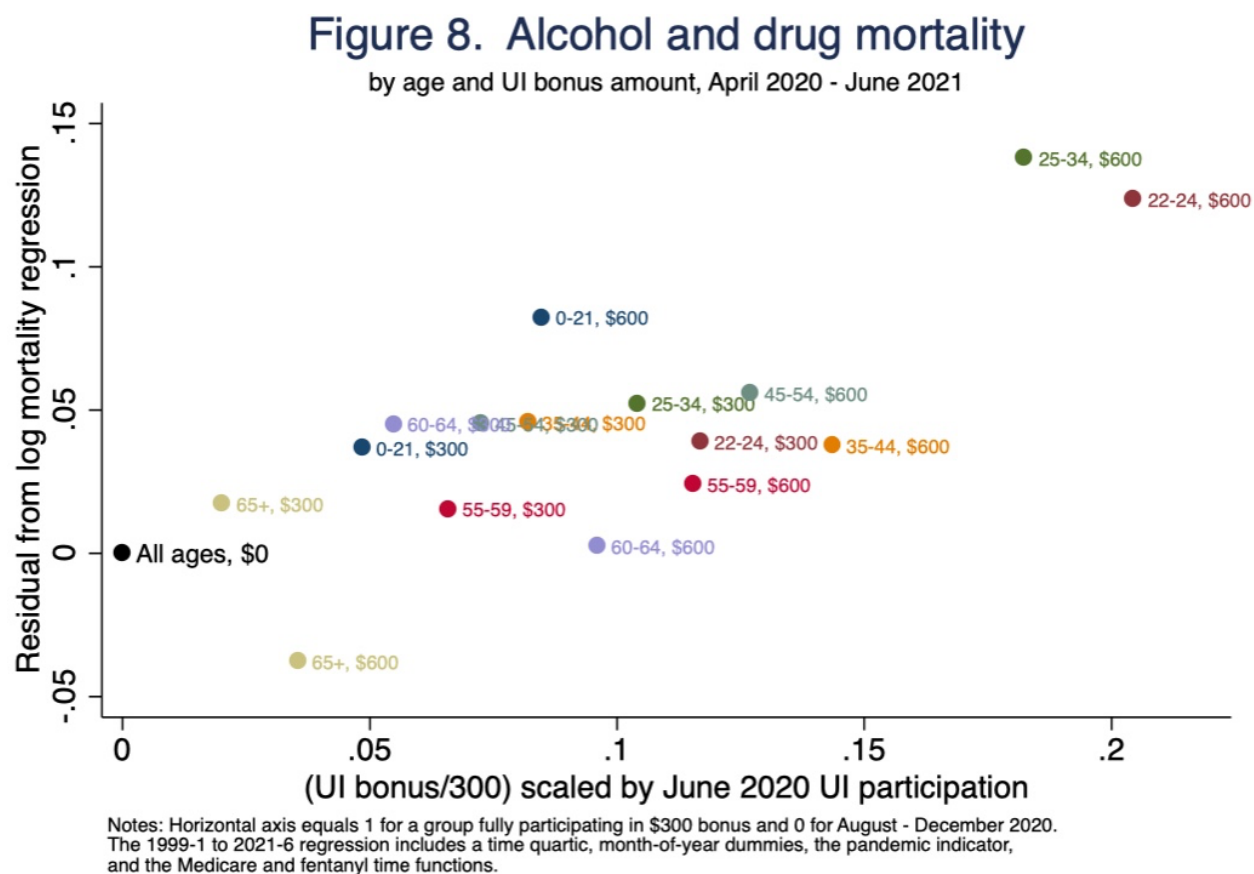
Because the eight-group average claimant ratio is 0.0705, we might expect the UI product variable to be the UI bonus coefficient scaled by $1/0.0705$, which is 0.38. In fact, the estimate is 0.39 and somewhat more statistically significant. The final two columns show how, as with the national specifications, the UI variable and the employment-population variable are not easily distinguished with the 1999-2021 mortality data alone. Relevant here, and consistent with the calibration approach, are the previous findings of Ruhm (2019), Case and Deaton (2020), and Currie and Schwandt (2020) of a weak short-run relationship between drug mortality and employment.

V.B. The dip in mortality in between UI-bonus episodes

Figure 8 shows more details of the month-age interactions for the months April 2020 through June 2021. By comparing alcohol and drug mortality (vertical axis) to the UI product variable (vertical axis), the figure shows how much mortality dipped during the \$0 bonus months that were chronologically in between the \$600 and \$300 bonus months. The figure's mortality variable was prepared from a OLS regression of log deaths (annual rate) on a time quartic, seasonals, age-group indicators, and the pandemic, Medicare and fentanyl indicators, where the observations are the eight age groups by 270 months. The residuals are averaged within age group and time period, of which I define three: April through July 2020 (\$600 bonus), August through December 2020 (no bonus) and January through June 2021 (\$300 bonus). Each of the 24 residual averages was then subtracted from the residual average for \$0 bonus period. This reduces the eight observations for August through December 2020 to a single point (the origin, labeled "All ages, \$0"). The remaining 16 observations are distinct points in Figure 8 showing

³⁹ U.S. Department of Labor (2021) and U.S. Census Bureau (2021). Although pandemic unemployment began in March 2020, several weeks were required for the state systems to absorb all of the claimants, which is why I use the demographic information from June 2020. DOL reports claimants "younger than 22" years old, which I assume to be aged 16-21 for the purposes of calculating a population denominator.

how much each age group's mortality and the UI variable were elevated during the \$600 and \$300 bonus periods.



With the exception of the elderly group, each age group had a V-shaped trend- and seasonally adjusted mortality series in 2020 and 2021 because all of the corresponding observations have positive mortality residuals.⁴⁰ Each tick on the vertical axis is 0.05, whose economic significance can also be assessed by comparing to the standard error of Table 3's aggregate mortality regressions (about half of 0.05). Mortality tends to be greater during the time periods when the bonus is \$600 rather than \$300. The two largest mortality residuals occur during the \$600 period for the two age groups receiving UI at the highest rates (22-24 and 25-

⁴⁰ Because Figure 8's mortality is measured as a residual from a regression including seasonals and a time quartic, it can be interpreted as seasonally-adjusted deviations from trend.

34). The V-shaped time series is not observed for suicide or, as suggested by Table 4, for alcohol. These patterns are no surprise from the perspective of the demand model.

VI. Conclusions

From the perspective of consumer-demand theory, it is no surprise that alcohol and drug mortality increased 20 to 30 percent above trend in the U.S. during the pandemic even while suicides did not increase. Nor is it a surprise that drug mortality followed a double-peaked time series, especially for age groups most likely to receive unemployment benefits during the pandemic. This paper uses pre-pandemic substitution patterns and a unit income elasticity to predict the timing and magnitude of mortality changes by substance (alcohol, narcotics, and meth).

The predictions are fairly close to the monthly data (Figure 8). Of the 40,000 drug and alcohol deaths above previous trend and seasonals between April 2020 and June 2021, the model predicts about 38,000, which are about evenly divided between income and substitution effects (Table 2). The modeled substitution effects are associated with substitution to low-price segments and reductions in the value of time. Both public policy and general concern for infectious disease resulted in substitution from drinking at bars and restaurants to drinking at home where alcohol is cheaper per gallon. For narcotics, income and value of time effects on demand put more expensive and less dangerous organic (and semi-synthetic) products in short supply, thereby pushing consumers to fentanyl that is cheaper, more elastically supplied, and more dangerous. Indeed, after an initial one-month spike, deaths involving heroin or prescription opioids fell significantly below prepandemic levels while deaths involving fentanyl and meth increased more than enough to increase drug deaths overall.

According to the model, drug deaths between April 2020 and June 2021 were about 11,000, corresponding to more than 400,000 life years lost, above trend due to the substitution effects of unemployment bonuses. Substitution to home alcohol consumption explains another 7,300 deaths corresponding to more than 200,000 life years. Moderate income effects of stimulus checks, rent moratorium and unemployment bonuses (less than one percent spent on

opioids or meth) explain another 20,000 alcohol and drug deaths or about 750,000 life years. This overall approach is consistent with the conclusions of Currie and Schwandt (2020), Council of Economic Advisers (April 2019), Ruhm (2019) and others that public policy can change rates of drug mortality over short periods of time.

This paper uses mortality data linked to alcohol and illicit drug consumption, which appear to be driven more by income and price changes rather than changes in demand at given prices. These findings do not contradict or confirm observations that the pandemic elevated feelings of depression and anxiety in the population (Panchal, et al. 2020), but do question the thesis that alcohol and especially drug mortality during the pandemic were primarily driven by new feelings of depression or loneliness (Galea, Merchant and Lurie 2020). Suicide did not increase in the U.S., while drug mortality fell sharply in the months between the \$600 and \$300 unemployment bonuses.

Narcotics, meth, and alcohol deaths were trending up prior to the pandemic at annualized rates of 6%, 24%, and 4%, respectively, as of December 2019. Part of the trends are due to increased diffusion of synthetic production methods into illicit drug markets, thereby reducing retail prices of both fentanyl and meth (Quinones 2021).⁴¹ Regardless of how the trends are explained, their contribution to deaths in 2020 and 2021 are dwarfed by the sudden increases above trend. The exception is meth deaths, which in 2019 contributed 20 percent to the sum of meth, narcotics, and alcohol.⁴²

Much remains unknown about drug markets during the pandemic. Data on the 2020 and 2021 prices and availability of prescription opioids, heroin, fentanyl, crystal meth, and other illicit drugs would sharpen the predictions of the demand-model approach. A comparison with smoking and gambling behavior would be of interest. Their income effects might be similar as for alcohol and illicit drugs, although the shift from bars and restaurants to home might produce different cigarette price changes than for alcohol because consumers purchase cigarettes at retail stores regardless of where they will be smoked. Health insurance participation can reduce the

⁴¹ The inflation-adjusted price of alcohol consumed at home has also trended down over time, although to a lesser degree (St. Louis Federal Reserve FRED series CUSR0000SEFW and CPIAUCSL).

⁴² My estimate of the income and substitution effects on meth mortality in 2020 and 2021 is less than my estimate of the increase resulting from trend alone.

out-of-pocket price of prescription opioids, increasing deaths involving prescription opioids while decreasing deaths involving fentanyl (the segment-substitution effect), although these effects may differ between public and private health insurance (Council of Economic Advisers April 2019).

Data from other countries would also be informative. Many countries also experienced reduced use of bars and restaurants, but had fewer if any increases in unemployment benefits or other transfers (Institute for Government 2022). In theory, the percentage increase in alcohol deaths in such countries would be almost as much as in the U.S. while the percentage increase in drug deaths would be much less. In the U.K. and Italy, it appears that alcohol mortality and consumption increased significantly whereas illicit drug consumption and mortality did not.⁴³

The evidence in this paper cannot by itself rule out the possibility that the agreements between theory and data are merely coincidental. However, if the income and substitution effects cited in this paper are not important factors, then we are left with several puzzles yet to be solved. One puzzle would be that overall alcohol and drug deaths increase so much while suicides and fatal heroin overdoses, which were formerly a significant fraction of “deaths of despair,” decreased. Another puzzle would be that deaths involving psychotropic drugs (especially, meth) increase in lesser proportions than both alcohol and narcotics deaths, even while some important narcotics categories do not increase. Other puzzles would include the double-peaked drug mortality time series as well as the pattern of mortality changes across age groups.

⁴³ See Office for National Statistics (2021a, 2021b) and Gili, et al. (2021). U.K. deaths from alcohol-specific causes increased 19 percent from 2019 to 2020, as compared to 15 percent in my demand model without income effect (substitution effect plus trend) and 26 percent in the U.S. data (Figure 6 of this paper). At the same time, deaths related to drug poisoning increased only 4 percent in England and Wales.

VII. Appendix I: Pre-2020 Trend Estimates by Substance

Table A1 displays the four mortality regressions – one for each of narcotics (T40), psychotropics (T43), alcohol-induced causes, and suicide – used to produce the dashed “trend plus seasonal” series in Figure 2. Time is measured in months and included in the regression as a quartic. The higher-order terms are normalized so that the monthly trend rate in December 2019 is the coefficient on the linear term.

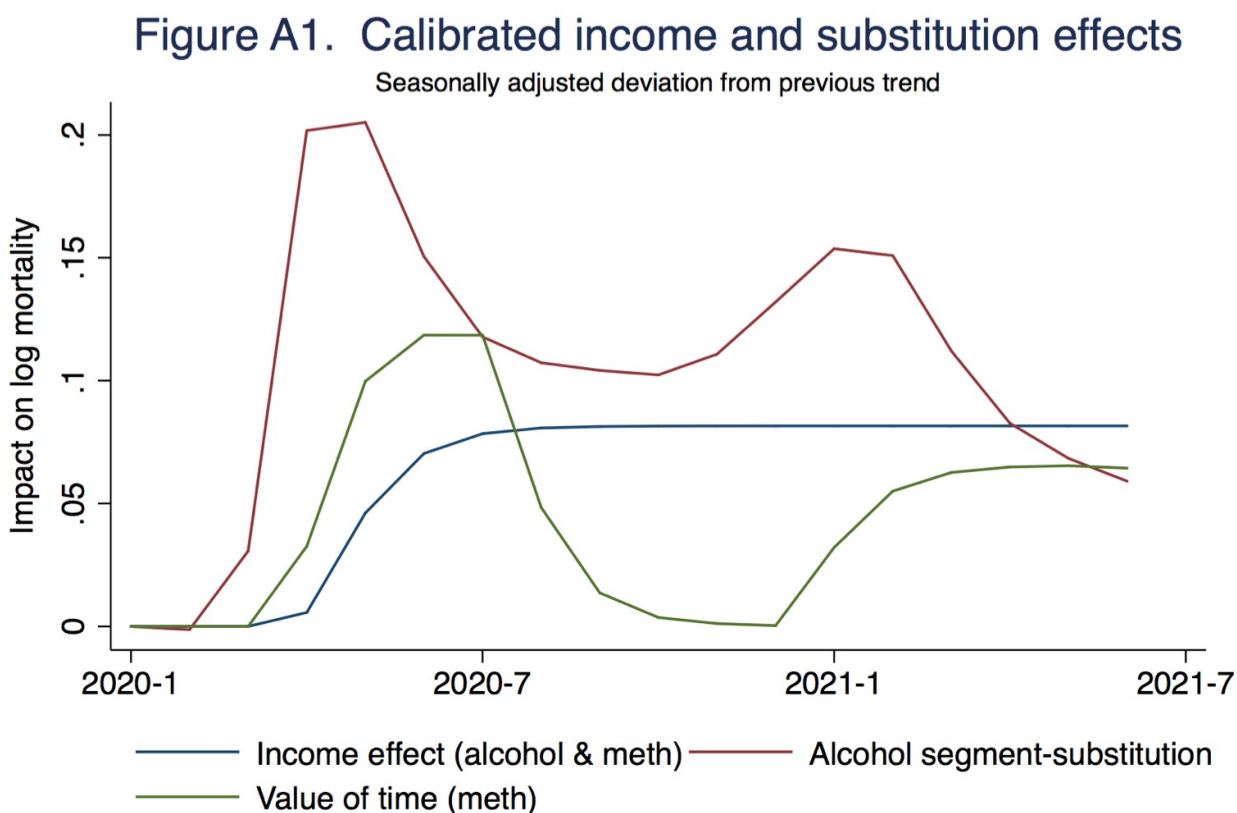
**Table A1. Coefficient point estimates from
Figure 2's "trend and seasonal" regressions**

OLS (1999-Jan through 2019-Dec) with dependent variable log annualized deaths

Regressor	Narcotics	Psychotropics	Alcohol	Suicide
Time (in months from 1960-Jan)	0.005	0.018	0.003	0.001
$[(\text{Time} - 2019\text{-Dec})/150]^2$	-0.93	1.01	-0.50	-0.56
$[(\text{Time} - 2019\text{-Dec})/150]^3$	-1.56	-0.55	-0.52	-0.42
$[(\text{Time} - 2019\text{-Dec})/150]^4$	-0.64	-0.44	-0.13	-0.10
Medicare (Time > 2005-Dec)	0.11			
Fentanyl (Time > 2015-Dec)	0.25			
February	0.055	0.036	-0.047	-0.008
March	0.037	-0.010	-0.067	0.027
April	0.022	0.009	-0.097	0.052
May	0.007	0.009	-0.119	0.058
June	-0.010	0.002	-0.111	0.057
July	-0.003	0.040	-0.104	0.059
August	-0.027	-0.009	-0.116	0.050
September	-0.046	-0.040	-0.113	0.034
October	-0.053	-0.076	-0.099	0.008
November	-0.044	-0.082	-0.072	-0.032
December	-0.037	-0.104	-0.031	-0.083
Constant	0.411	-9.399	1.619	2.282
Std. error of the regression	0.068	0.077	0.025	0.029
Observations	252	252	252	252

VIII. Appendix II: Demand-model Sensitivity Analysis

The demand specification in the main text assumes a monthly lag parameter of $\lambda = \frac{3}{4}$, a time requirement for ordinary consumption that is half that for drug consumption, and that the marginal propensity to spend income windfalls on abused substance is (among those at risk of consuming those substances) $m = \frac{1}{2}$ within 18 months. Figure A1 shows the increments to each month's meth and alcohol mortality (in logs) implied by these benchmark parameters. As discussed in the main text (especially Table 1), the increments to narcotics mortality are the meth increments scaled by a factor of $1/(1-0.47)$.

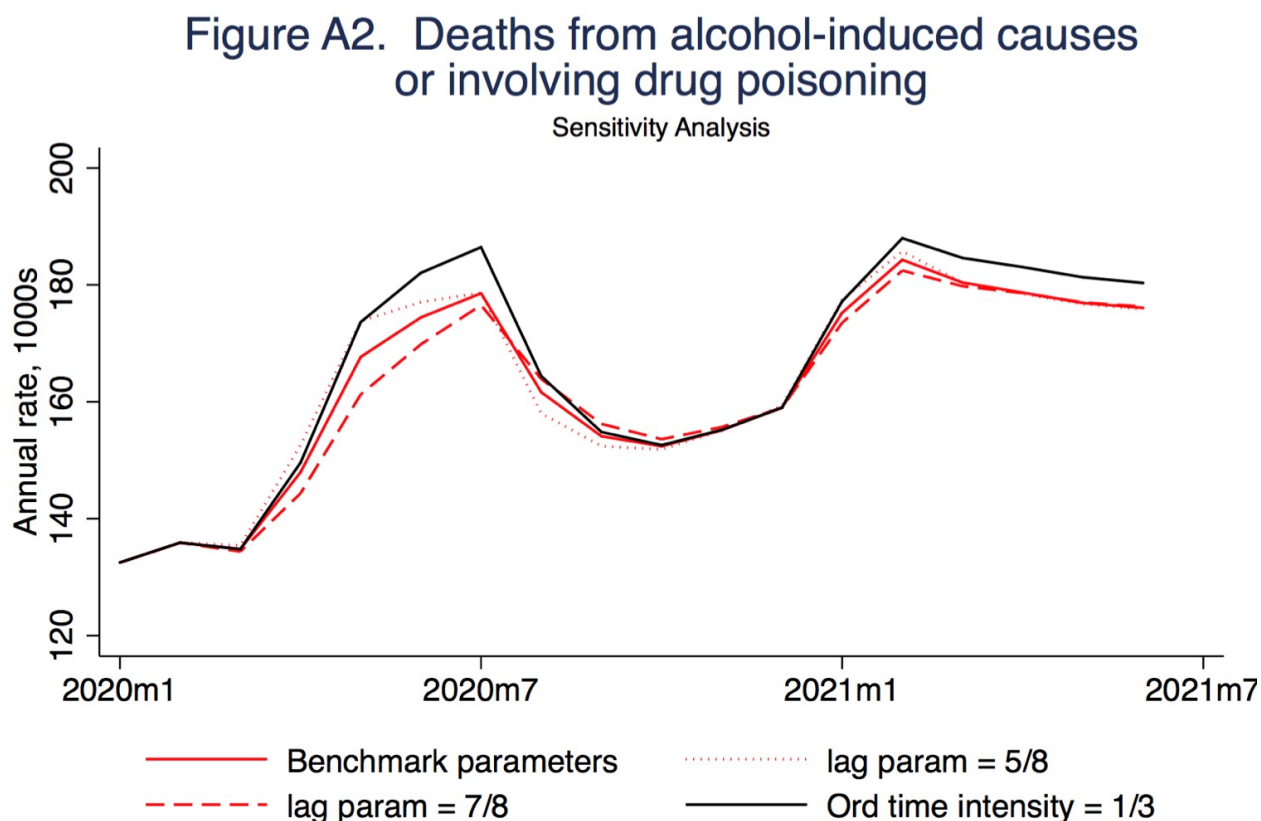


Note: Impacts on narcotics are the meth impacts scaled by the narcotics segment-substitution factor.

One row of Table 2 shows demand predictions alternatively assuming $m = 0$ (no income effect). Recall from the main text that the income effect scales demand by a weighted average of $(1+gm)/(1-rm)$ for tenants (27 percent) and $(1+gm)$ for the others (73 percent), which is a factor of 1.085 at the benchmark parameters. Replacing $m = 1$ results in a factor of 1.185, which would

rescale Figure A1's income-effect series by a factor of 2.1. That is, $m = 1$ results in about doubling the income effect on mortality as the benchmark $m = \frac{1}{2}$ does.

Figure A2 shows alternatives of $\lambda = 5/8$, $\lambda = 7/8$, and an ordinary consumption of $1/3$ drug consumption.



Notes: The benchmark weekly lag parameter is $3/4$. The benchmark relative time intensity of ordinary consumption is $1/2$.

The narcotics segment substitution effect modeling in this paper holds constant the quantity of consumption in the high-priced narcotics segment, which appears to well approximate the U.S. mortality data in 2020 and 2021 (Figure 3). To the extent that the segment has price-elastic supply in the short run, the segment substitution effect is less and therefore would move Figure 4's narcotics-model series (includes a segment-substitution effect) toward Figure 4's meth-model series (no segment substitution effect).

IX. Appendix III: Inferring Substance Abuse from Mortality Data

Substance abuse is as defined in the National Surveys on Drug Use and Health (NSDUH), where it is referred to as “substance use disorder for specific substances.” My general approach is to estimate the ratio of the number of individuals with substance use disorder (a “stock”) to annual deaths (a “flow”) in 2018 and 2019 and apply that substance-specific ratio to substance-specific deaths in 2020 and 2021. Because NSDUH is known to undercount substance abuse, I adjust the narcotics and meth ratios using studies of opioid undercounts, as explained below.

NSDUH reports 14.818 million and 14.504 million persons with alcohol use disorder in 2018 and 2019, respectively (Substance Abuse and Mental Health Services Administration 2020). Mortality from alcohol-induced causes (Figure 2 of this paper) was 37,329 and 39,043, respectively. The ratio of 383.9365 of average number with substance use disorder to average annual mortality is applied to Table 2’s alcohol mortality (after annualizing it) to obtain 19.9 million persons with alcohol use disorder at an average point in time between April 2020 and June 2021.

Barocas et al. (2018) use a multisample stratified capture-recapture approach to measure opioid use disorder in Massachusetts in each of the years 2011-15. I use the years 2014 and 2015, when on average the state had 254,127 persons with opioid use disorder, because they were the first years that Massachusetts was experiencing significant numbers of deaths involving fentanyl. CDC Wonder shows an annual average number of Massachusetts death certificates involving opioids (TCodes T40.0 through T40.4) of 1,538. I use their ratio (165.2321) to convert all T40 deaths in Table 2 (annualized) into 13.4 million persons with narcotics use disorder at an average point in time between April 2020 and June 2021.⁴⁴

In order to convert meth deaths into persons with meth use disorder, I assume that NSDUH undercounts opioid and meth use at the same rates. In other words, when combined

⁴⁴ Note that 89 (92) percent of 2019 (2020) death certificates citing any T40 code cited opioids, respectively.

with the death certificate data, NSUDH provides an accurate estimate of the relative mortality risks of opioid and meth use disorders even while overestimating their levels. Using NSDUH's estimates of heroin and pain-reliever use disorders (fentanyl is not measured), I estimate that opioid use disorder is 2.3 times as deadly and therefore use a ratio of 376.005 to convert meth mortality to meth use disorder. In other words, as of 2018 and 2019 meth use disorder and alcohol use disorder appear to have similar mortality rates, which are less than the mortality rates associated with opioids.

By 2020, the number of people with meth use disorder was about the same as those with opioid use disorder (Table 2), which suggests that expenditure on opioids and meth is approximately double opioid expenditure, which was roughly \$25 billion over a 15-month period (Mulligan 2020). If the income effect of fiscal transfers increased these expenditures by 10 percent, that would be \$5 billion additional spending on opioids and meth, which is easily less than one percent of the more than \$2 trillion in transfers.

XI. Bibliography

- Alexander, Monica J., Mathew V. Kiang, and Magali Barbieri. "Trends in black and white opioid mortality in the United States, 1979–2015." *Epidemiology (Cambridge, Mass.)* 29 (2018): 707.
- Alpert, Abby, David Powell, and Rosalie Liccardo Pacula. "Supply-side drug policy in the presence of substitutes: Evidence from the introduction of abuse-deterrent opioids." *American Economic Journal: Economic Policy* 10 (2018): 1–35.
- American Addiction Centers. "Meth Addiction: Facts, Statistics & How Meth Changes You." *americanaddictioncenters.org*. July 7, 2021. <https://americanaddictioncenters.org/meth-treatment/facts>.
- Barocas, Joshua A., et al. "Estimated prevalence of opioid use disorder in Massachusetts, 2011–2015: a capture–recapture analysis." *American Journal of Public Health* 108 (2018): 1675–1681.
- Barro, Robert J. "Are Government Bonds Net Wealth?" *Journal of Political Economy* 82, no. 6 (December 1974): 1095–1117.
- Becker, Gary S. "A Theory of the Allocation of Time." *Economic Journal* 75, no. 299 (September 1965): 493–517.
- Becker, Gary S. "Irrational behavior and economic theory." *Journal of political economy* 70 (1962): 1–13.
- Brody, Jane E. "High Functioning, but Still Alcoholics." *New York Times*, May 4, 2009.
- Case, Anne, and Angus Deaton. *Deaths of Despair and the Future of Capitalism*. Princeton University Press, 2020.
- Centers for Disease Control and Prevention. "Behavioral Risk Factor Surveillance System." *cdc.gov*. October 8, 2021. <https://www.cdc.gov/brfss/index.html>.
- . "Provisional Mortality Statistics." *covid.cdc.gov*. January 6, 2022. <https://wonder.cdc.gov/wonder/help/mcd-provisional.html>.
- Conway, Jan. "Average annual expenditure on alcoholic beverages per consumer unit in the United States in 2019, by category (in U.S. dollars)." *statistica.com*. June 4, 2021. <https://www.statista.com/statistics/255473/us-consumer-expenditure-on-alcoholic-beverages-by-category/>.
- Council of Economic Advisers. *The Role of Opioid Prices in the Evolving Opioid Crisis*. Executive Office of the President, April 2019.

- Currie, Janet, and Hannes Schwandt. "The Opioid Epidemic Was Not Caused by Economic Distress But by Factors that Could be More Rapidly Addressed." *NBER working paper*, no. 27544 (August 2020).
- Currie, Janet, Jonas Jin, and Molly Schnell. "US Employment and Opioids: Is There a Connection?" In *Health and Labor Markets*, by Solomon W. Polachek and Tatsiramos Konstantinos, 253-80. Bingley, UK: Emerald Publishing Limited, 2019.
- Evans, David K., and Anna Popova. "Cash transfers and temptation goods." *Economic Development and Cultural Change* 65 (2017): 189–221.
- Evans, William N., Ethan M. J. Lieber, and Patrick Power. "How the reformulation of OxyContin ignited the heroin epidemic." *Review of Economics and Statistics* 101 (2019): 1–15.
- Florence, Curtis, Feijun Luo, and Ketra Rice. "The economic burden of opioid use disorder and fatal opioid overdose in the United States, 2017." *Drug and alcohol dependence* 218 (2021): 108350.
- Frone, Michael R. *Alcohol and illicit drug use in the workforce and workplace*. American Psychological Association, 2013.
- Galea, Sandro, Raina M. Merchant, and Nicole Lurie. "The mental health consequences of COVID-19 and physical distancing: the need for prevention and early intervention." *JAMA internal medicine* (American Medical Association) 180 (2020): 817–818.
- Gallet, Craig A. "Can price get the monkey off our back? A meta-analysis of illicit drug demand." *Health economics* 23 (2014): 55–68.
- Gallet, Craig A. "The demand for alcohol: a meta-analysis of elasticities." *Australian Journal of Agricultural and Resource Economics* 51 (2007): 121–135.
- Gili, Alessio, et al. "Changes in Drug Use Patterns during the COVID-19 Pandemic in Italy: Monitoring a Vulnerable Group by Hair Analysis." *International Journal of Environmental Research and Public Health* 18 (2021).
- Google. "COVID-19 Community Mobility Reports." *google.com*. December 2021. <https://www.google.com/covid19/mobility/>.
- Goolsbee, Austan, and Chad Syverson. "Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020." *Journal of public economics* 193 (2021): 104311.
- Gordon, Will. "Why The Hell Does Your Drink Cost So Much?" *deadspin.com*. November 1, 2013. <https://deadspin.com/why-the-hell-does-your-drink-cost-so-much-1454231900>.
- Herttua, Kimmo, Pia Mäkelä, and Pekka Martikainen. "Changes in alcohol-related mortality and its socioeconomic differences after a large reduction in alcohol prices: a natural

- experiment based on register data." *American journal of epidemiology* 168 (2008): 1110–1118.
- Institute for Government. "Coronavirus: how different countries supported the unemployed." *instituteforgovernment.org.uk*. January 10, 2022.
<https://www.instituteforgovernment.org.uk/explainers/coronavirus-unemployment-support>.
- Koski, Anna, Reino Sirén, Erkki Vuori, and Kari Poikolainen. "Alcohol tax cuts and increase in alcohol-positive sudden deaths—a time-series intervention analysis." *Addiction* 102 (2007): 362–368.
- Leon, David A., et al. "Hazardous alcohol drinking and premature mortality in Russia: a population based case-control study." *The Lancet* 369 (2007): 2001–2009.
- Mallatt, Justine. "The effect of prescription drug monitoring programs on opioid prescriptions and heroin crime rates." *Available at SSRN 3050692*, 2018.
- Mulligan, Casey B. "Prices and Federal Policies in Opioid Markets." *NBER working paper*, no. 26182 (February 2020).
- Mulligan, Casey B. "Prices and Policies in Opioid Markets." *manuscript, University of Chicago*, February 2021.
- . *The Redistribution Recession*. New York: Oxford University Press (redistributionrecession.com), 2012.
- National Center for Health Statistics. "Multiple Cause of Death Data Files." *cdc.gov*. 1999-2019.
<https://www.cdc.gov/nchs/nvss/deaths.htm>.
- Nemtsov, Alexander V. "Alcohol-related human losses in Russia in the 1980s and 1990s." *Addiction* 97 (2002): 1413–1425.
- New Strategist. *Who's Buying Alcoholic and Nonalcoholic Beverages*. 11th. New Strategist Press, 2015.
- OECD. "Housing Costs over Income." *OECD Affordable Housing Database*. February 2021.
<https://www.oecd.org/els/family/HC1.2-Housing-costs-over-income.xlsx>.
- Office for National Statistics. "Alcohol-specific deaths in the UK: registered in 2020." *ons.gov.uk*. December 7, 2021b.
<https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/causesofdeath/bulletins/alcoholrelateddeathsintheunitedkingdom/registeredin2020>.
- . "Deaths related to drug poisoning in England and Wales: 2020 registrations." *ons.gov.uk*. August 3, 2021a.

- <https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/bulletins/deathsrelatedtodrugpoisoninginenglandandwales/2020>.
- Panchal, Nirmita, et al. "The implications of COVID-19 for mental health and substance use." *Kaiser family foundation* 21 (2020).
- Parrott, Jim, and Mark Zandi. "Averting an Eviction Crisis." *urban.org*. January 2021. <https://www.urban.org/sites/default/files/publication/103532/averting-an-eviction-crisis.pdf>.
- Petry, Nancy M. "Delay discounting of money and alcohol in actively using alcoholics, currently abstinent alcoholics, and controls." *Psychopharmacology* 154 (2001): 243–250.
- Powell, David, Abby Alpert, and Rosalie L. Pacula. "A transitioning epidemic: how the opioid crisis is driving the rise in hepatitis C." *Health Affairs* 38 (2019): 287–294.
- Quinones, Sam. *Dreamland: The true tale of America's opiate epidemic*. New York: Bloomsbury Publishing USA, 2015.
- . *The Least of Us: True Tales of America and Hope in the Time of Fentanyl and Meth*. Bloomsbury Publishing USA, 2021.
- Ridout, Kathryn K., et al. "Emergency department encounters among youth with suicidal thoughts or behaviors during the CoViD-19 pandemic." *JAMA psychiatry* 78 (2021): 1319–1328.
- Ruhm, Christopher J. "Corrected US opioid-involved drug poisoning deaths and mortality rates, 1999–2015." *Addiction* 113 (2018): 1339–1344.
- Ruhm, Christopher J. "Drivers of the fatal drug epidemic." *Journal of health economics* 64 (2019): 25–42.
- Saffer, Henry, and Frank Chaloupka. "Alcohol tax equalization and social costs." *Eastern Economic Journal* 20 (1994): 33–43.
- Schnell, Molly. "The Economics of Physician Behavior." *Princeton University PhD Dissertation*, 2018.
- Schulfer, Scott. "Wine Price: Wine Bottle Price and Restaurant Wine Markup." *binwise.com*. December 19, 2019. <https://home.binwise.com/blog/how-to-price-wine-bottles>.
- Social Security Administration. "Period Life Tables: Projected." *ssa.gov*. September 2021. <https://www.ssa.gov/oact/HistEst/PerLifeTables/2021/PerLifeTables2021.html>.
- Soni, Aparna. "Health Insurance, Price Changes, and the Demand for Pain Relief Drugs: Evidence from Medicare Part D." *Kelley School of Business Research Paper*, 2018.

Spillane, Susan, et al. "Trends in alcohol-induced deaths in the United States, 2000-2016." *JAMA network open* 3 (2020): e1921451–e1921451.

Substance Abuse and Mental Health Services Administration. "Substance Use Disorder for Specific Substances in Past Year among Persons Aged 12 or Older, by Age Group." *samhsa.gov*. 2020.
<https://www.samhsa.gov/data/sites/default/files/reports/rpt29394/NSDUHDetailedTabs2019/NSDUHDetTabsSect5pe2019.htm>.

Treisman, Daniel. "Death and prices: The political economy of Russia's alcohol crisis 1." *Economics of transition* 18 (2010): 281–331.

U.S. Census Bureau. "Table 1. Total U.S. Resident Population by Age, Sex, and Series: April 1, 2020." *www2.census.gov*. 2021. <https://www2.census.gov/programs-surveys/popest/tables/2020/2020-demographic-analysis-estimates/table-1.xlsx>.

United States Department of Labor. *Characteristics of the Insured Unemployed*. 2021.
<http://www.ows.doleta.gov/unemploy/chariu.asp>.

United States Internal Revenue Service. "Third Economic Impact Payment." *irs.gov*. December 2021. <https://www.irs.gov/coronavirus/third-economic-impact-payment>.

—. "Treasury and IRS begin delivering second round of Economic Impact Payments to millions of Americans." *irs.gov*. December 2020. <https://www.irs.gov/newsroom/treasury-and-irs-begin-delivering-second-round-of-economic-impact-payments-to-millions-of-americans>.

Waggoner, John. "What Is the IRS Timeline to Send the Third Stimulus Checks?" *aarp.org*. May 27, 2021. <https://www.aarp.org/money/taxes/info-2020/irs-timeline-to-send-stimulus-funds.html>.