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Labor market insertion as a way of combatting the root causes of fentanyl addiction

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Abstract

Fentanyl addiction is a latent epidemic in the United States that claims thousands of lives annually. This crisis has been driven by population and economic factors. A linear regression model was used to quantify the impact and significance of some of these variables on the magnitude of the epidemic, measured by the number of fentanyl overdose deaths per 100,000 inhabitants. A sample of 29 U.S. states was taken. Three statistically significant variables, as mentioned in the literature, were used: per capita health expenditure, the unemployment rate, and the percentage of the population between 15 and 34 years old. Coefficients were obtained that relate a series of independent variables to the mentioned measure. The most relevant finding was a positive coefficient of 6.620 for each percentage point increase in the unemployment rate. The cause of this result could be explained through the theory of the availability of alternative rewards in the development of addictions. This suggests that public policy aimed at job placement could be effective in addressing the crisis.

Key Words

Fentanyl, addicition, unemployment.

Clasificación JEL: E24, J01, J02, J41.

Introduction

Fentanyl has caused a drug addiction epidemic that has plagued the United States of America since 2013. It is a synthetic opioid, characterized by generating a high degree of chemical dependence in the brain, and is considered to be 50 times stronger than its chemical relative: heroin (DEA, n.d.). Although it started as a painkiller, fentanyl is now one of the most widely traded drugs on the illegal market. The sale of this narcotic is extremely lucrative, with prices reportedly reaching up to $800 per kilogram (Ethic, 2023).

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The entire United States has recorded deaths from unintentional overdoses of this chemical. In 2023 alone, 51,285 U.S. citizens died due to this narcotic (CDC, 2024). Brian Clark, a DEA agent, considers this drug one of the deadliest for addicts and the cause of one of the worst crises across the United States.

In response to the crisis, each U.S. state has adopted a different public policy approach. For example, New York has chosen to distribute medications useful in the event of an overdose in educational institutions of all kinds (Elsen-Rooney, 2024). In contrast, Ohio has established prison sentences of up to 12 months for those caught in possession of fentanyl (Zuckerman, 2024). Meanwhile, California has launched educational campaigns (Kennedy, 2024).

Some states, such as Oregon, have failed to control the crisis and have been forced to declare states of emergency in their major cities, despite having combined a wide variety of public rehabilitation programs for fentanyl addicts (BBC, 2024).

The crisis becomes more pressing every day. Currently, more than half of all overdoses are due to fentanyl (CDC, 2024). The causes of the epidemic have been studied; however, expert opinion is divided. One group, represented by the RAND Foundation and including names such as Beau Kilmer and Roland Neil (2024), has attributed the crisis to a lack of police oversight and poor enforcement of anti-narcotics laws.

Another possibility is that the crisis stems from educational deficiencies. According to the perspective offered by the Columbus Foundation (2022), educating young people is enough to reduce the consumption of harmful fentanyl. Along the same lines of thought, the Arista Recovery Foundation (2025) argues that young people who are properly informed about the issue do not tend to develop drug addictions. However, this is not a claim that has been fully verified.

Alternatively, the considerable number of deaths has been attributed to a poorly funded healthcare system, incapable of providing adequate care to those suffering from substance abuse disorders. This idea is supported by Carlos Blanco (2023), director of the U.S. National Institute on Drug Abuse (NIDA). He has called for a comprehensive improvement of the healthcare system in order to halt the fentanyl addiction epidemic.

Also noteworthy is the stance of Nolte-Troha et al. (2023), who identify the origins of the epidemic in the precarious labor conditions and unemployment experienced by many

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Americans. These authors argue that an individual's socioeconomic circumstances are the most important factor in the development of addictions, as they are a central psychological stressor for the majority of the population.

This variety of possible causes for the epidemic raises several questions. Mainly: is there a statistically significant and clearly identifiable factor driving the fentanyl crisis in the United States? This article proposes a linear regression model, which highlights correlations between various economic and population factors and the number of unintentional fentanyl overdose deaths across a sample of 29 U.S. states.

In addition to the introduction, this article is structured as follows. The first section presents a review of the existing literature. The second outlines the methodology related to linear regression models. The third presents the results along with their respective discussion. Finally, the conclusions are presented, emphasizing the main findings and the limitations of the proposed analysis.

Literature review

Socioeconomic factors correlated with drug use

The study of addiction has been the focus of various scientific articles. Although few focus solely on fentanyl, there is a large body of literature that takes a more general approach, extending to drugs as a whole or, more broadly, to the chemical family of opioids.

The development of a fentanyl consumption crisis depends on factors intrinsic to a community, independent of government decisions directly related to the issue. The Gateway Foundation (2024) states that some of these variables include: population density, the number of medically prescribed opioids, and the level of wealth. Various studies may support these claims.

First, Noguera (2000) highlights that psychologically stressful conditions—inseparable from life in densely populated areas—can lead to widespread drug use. This suggests that as the population of a given area (for example, a state) increases, so too does the prevalence of drug use.

Second, Cicero et al (2017) observed that nearly half of the opioid addicts who responded to the Survey of Key Informants' Patients—a representative sample of patients seeking rehabilitation across 49 U.S. states—had their first exposure to such substances through a medical prescription. However, these results might differ when fentanyl is considered separately from other opioids. Jones et al. (2021) argue that there is a positive correlation between the reduction in opioid prescription rates for medical purposes and the proportion of deaths due to fentanyl in relation to the total number of opioid-related deaths. These authors conducted their studies on a sample of Canadian provinces using data from 2011–2018, and they claim that the correlation they found has less than a 5% probability of being a random occurrence.

Third, the economic factors that may lead to the development of addictions have also been studied. Baptiste-Roberts and Hossain (2018) analyzed data from the 2013 edition of the National Survey on Drug Use and Health and found that individuals in the bottom 10% of a community’s income distribution had a higher probability of using drugs. These authors found that a person in the lowest income decile was 1.36 times more likely to use drugs than an individual in the highest income decile.

Similarly, Dow et al. (2020), using data from the CDC and the U.S. Census Bureau (USCB), concluded that increasing the minimum wage and expanding tax refunds for low-income individuals would reduce overdose deaths. A complementary study by Wilkinson and Pickett (2011) categorizes social inequality as a determinant of drug addiction levels.

Another relevant economic factor, closely linked to social inequality, is long-term unemployment. This argument is supported by the analysis of Compton et al. (2014). Using data from the National Survey on Drug Use and Health, which is representative of the entire adult U.S. population, these authors concluded that there is a correlation between substance use and lack of employment.

Also, among economic factors, some authors have identified that drug consumption tends to decrease when prices increase. Specifically, Chaloupka et al. (1999) reported a price elasticity of -1.28 for cocaine.

Additionally, studies have been conducted on individual factors that may promote the majority of chemical dependency disorders, including fentanyl addiction. For example, Vasilenko et al. (2018) concluded that, in the case of opioids, the general tendency toward addiction decreases with age (in addition to depending on other demographic factors such as biological sex). This conclusion was reached through analysis of data from the National Epidemiologic Survey on Alcohol and Related Conditions (NESARC), which is representative of the entire adult U.S. population. The authors note that opioid use tends to increase dramatically during early adulthood, then decreases, rises slightly around age 50, and declines steadily after that point in individuals’ lives.

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Szalavitz (2015) offers a biological explanation for this trend. She notes that the MECP2 gene, which causes the lack of impulse control characteristic of drug addiction disorders, is especially active during youth. This implies that young people are more prone to consuming harmful substances regardless of the policies adopted in their communities. Szalavitz also points out that more than 50% of addiction disorders are due to genetic factors that are not yet fully understood.

Finally, there are family and social conditions that may foster addiction. Marziali et al. (2023) found that the interpersonal relationships of American adolescents influence their likelihood of becoming frequent users of narcotics. The authors identified that young people who have trusting social relationships and whose friends or parents show a negative attitude toward drug use are less likely to become users of harmful substances such as alcohol, tobacco, and marijuana.

The effects of public spending on drug addiction

The study of addiction-related public policy has been the focus of numerous investigations, as it is a relevant economic factor that warrants thorough analysis. Specifically, Douglas and Rangel (2005) analyzed a variety of controlled neuroscientific experiments and inferred that the most effective policies are those that help individuals self-regulate. Additionally, they assert that criminalization policies can be effective, but their success depends on whether individuals make rational decisions to either use or abstain from drug consumption.

The authors also emphasize the effectiveness of "cognitive" policies—those that regulate the signals individuals receive from their environment that falsely suggest drug use will result in a net benefit. One example of such signals is advertising that promotes the use of legal drugs. Moreover, these researchers caution that better education does not necessarily lead to a reduction in addiction, since even a well-informed individual may still live in an environment that conditions them toward addiction.

Also questioning the role of education, Johnson et al. (2009) analyzed data from the Minnesota Twin Family Study (a social behavior study conducted on twins in the state of Minnesota in 1983) and discovered a positive correlation between education level and the use of harmful substances. The authors attribute this observation to other factors—either genetic or cultural—rather than a direct causal relationship, identifying such link as spurious.

However, Midford (2000) argues that the correlation between drug abuse and education tends to become clearer when specific educational programs aimed at informing youth about addiction are evaluated. The researcher found that such programs have an observable impact—albeit one that tends to diminish over time—on their target population. He notes that the effectiveness of these initiatives depends on the quality of their instructional design and their alignment with the available evidence on drugs.

Other authors have focused their research not on the effects of education, but rather on the impact of the healthcare system on addiction levels in the American population. For example, Krawczyk et al. (2020) studied a sample of 48,274 residents of Massachusetts and concluded that treating opioid addiction with medications that chemically mitigate addiction reduces mortality among users more effectively than non-medication-based treatments. Independently, Bahji and Bajaj (2018) identified a similar trend in the Canadian population, based on 2016 statistics.

Likewise, Barry (2017) compiled and identified trends in data from the U.S. Vital Statistics Administration regarding fentanyl abuse in the state of Maryland, covering the years 2007–2015. Based on this data, the psychiatrist concluded that pharmacological treatment, in combination with specific types of psychological therapy, is an effective way to prevent overdoses. He also asserts that the availability of rehabilitation options does not act as a positive incentive for developing addictions.

On the other hand, Mark and Huber (2024) observed that individuals insured under Medicaid—a healthcare program that includes treatment for addiction through medications and psychological care—had a higher overdose mortality rate than the general population. In 2020, those insured under Medicaid recorded a rate of 54.6 overdose deaths per 100,000 inhabitants, while the national rate for the United States as a whole was 27.9. This finding has not yet been fully explained.

Given the lack of definitive conclusions in the areas of health and education, researchers have explored the possibility of adopting a law enforcement-based approach to combat illegal trafficking. In this regard, Neil and Kilmer (2024) analyzed national arrest data from 2010 to 2022. These statistics were provided by the U.S. Bureau of Justice Statistics (BJS). The authors highlight the crucial role of local police in halting drug trafficking, thereby limiting the supply available to addicts and helping to control the epidemic.

Conversely, a study by the Pew Foundation (2018) concluded that imprisonment for drug possession shows no correlation with the number of overdose deaths or with reported drug use levels among the population. This implies that arrests do not help control the epidemic.

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The analysis was based on data from the BJS and the Federal Bureau of Prisons, using 2014 data and covering the entire United States.

Some authors propose the effectiveness of a comprehensive policy that includes the areas of healthcare, education, and law enforcement. In this category, Blanco et al. (2020) stand out. After reviewing a considerable amount of literature on the topic, they concluded that fentanyl policy must be integrated and encompass all sociological aspects that can foster consumption within the U.S. population. The risk variables mentioned by the authors align with those discussed in this review.

Finally, Caulkins et al. (1999) compared the costs and efficiency of various types of public policy aimed at combating cocaine addiction. The authors estimated the reduction in kilograms (kg) of cocaine consumption per million dollars of government spending on a given program. For educational programs, they estimated a reduction of about 25 kg per million spent (considering they have a moderate effect on youth), and for law enforcement programs, they reported similar effectiveness. In contrast, they argued that public investment in treatment is more cost-effective, estimating that each million dollars spent in this area reduces youth consumption by 100 kg.

Economic models descriptive of addictive behavior

There are various economic theoretical frameworks that attempt to explain why addictions occur. One of the most widely used paradigms is the rational addiction model proposed by Becker and Murphy (1988). Broadly speaking, this model consists of a detailed consumption plan formulated by the individual over the course of their life, with the intention of maximizing total utility (consuming only up to the point it generates pleasure), while prioritizing immediate gratification. However, this approach has been criticized by Rogeberg (2004), who argues that it is not logically consistent with most available empirical observations.

Considering such criticisms, alternative models have been developed that are similar to rational addiction but relax the assumption of perfect rationality. The most relevant examples include Simon's (1957) theory of bounded rationality and the prospect theory paradigm introduced by Kahneman et al. (1979).

An alternative conceptual framework to rational addiction is the one proposed by Parfit (1984). The author presents a game theory model in which the addicted individual competes with their future (non-addicted) self. The addicted self gains utility from consumption, while the non-addicted self gains utility by reducing consumption. For both selves, the costs outweigh the benefits.

A third approach is the hyperbolic discounting model developed by Harris and Laibson (2012). This model suggests that although individuals make decisions with their future in mind and understand that quitting drug use is in their rational interest, their preferences are inconsistent, and they tend to discount future utility in a hyperbolic manner. This leads them to postpone the decision to reduce or eliminate their consumption.

The common element among these three models—examples of the most commonly used approaches in behavioral economics—is that addicted individuals tend to value present utility more than future utility. It is worth noting that this document does not cover all existing models; the examples presented here represent only a portion of the available literature.

Data and methods

In order to design a statistically significant model that includes factors mentioned in the previous literature, a set of variables was selected, as presented in Table 1:

Table 1
Data and variables

Algebraic symbol	Variable	Source
Y_i	Number of fentanyl overdose deaths. Rate per 100,000 residents	Official CDC data: presented through the data collection system known as the State Unintentional Drug Overdose Reporting System (SUDORS).
X_1	*Per capita* health expenditure in thousands of dollars	Official data from the U.S. Census Bureau (USCB), compiled through the Annual Survey of State Government Finances
X_2	Percentage of the population that are between 15 and 34 years of age	Data from the American Community Survey (Table S0101), reported by the U.S. Census Bureau (USCB). The estimates used are based on five-year data
X_3	Unemployment rate in percentage points	Data from the U.S. Bureau of Labor Statistics (BLS).

Source: Author´s own work

It is important to note that the data were obtained for a sample of 29 U.S. states, these states were: Arizona, Colorado, Connecticut, Delaware, Georgia, Iowa, Kansas, Kentucky, Maine, Maryland, Massachusetts, Michigan, Minnesota, Montana, Nebraska, Nevada, New

Hampshire, New Jersey, New Mexico, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, Tennessee, Utah, Vermont, Virginia, and West Virginia. This selection was based on the availability of comparable data within the sample group. Only data from the year 2022 were considered.

For the variables Y_i and X_1 raw data were obtained and adjusted to account for population size. The population estimates used for this adjustment come from the 2022 edition of the American Community Survey (Table B01003), compiled by the U.S. Census Bureau (USCB), based on five-year estimates.

Addiction levels were measured using the rate of fatal overdoses per 100,000 inhabitants, under the assumption that higher addiction levels within a community will be reflected in a higher mortality rate.

It is also relevant to point out that the selection of independent variables was initially based on the inclusion of all variables mentioned in the literature for which data were available within the chosen sample. However, some regressors were removed after being found statistically insignificant. The selection criterion was based on the Ssudent's t-test at a 95% confidence level (see methodology), using backward stepwise elimination.

The excluded variables were: per capita public spending on police departments, per capita public spending on education, the percentage of the population aged between 34 and 64 years, per capita GDP for 2022, the fraction of the population incarcerated in 2022, the state-level Gini index for 2022, and the share of the state population prescribed opioids in 2022. Despite their exclusion from the model, these variables may still play a role in the phenomenon under study (see discussion). Lastly, all computations were performed using R Studio, version 4.4.1.

Methodology

The aim of this analysis is to examine the impact of various socioeconomic factors on the number of fentanyl overdose deaths reported across different U.S. states. The method used was Ordinary Least Squares (OLS).

To begin, two basic concepts from linear regression techniques are required. The first is the intuitive interpretation of the slope estimated between a dependent variable and an independent variable. The second is the statistical significance of the impact of a regressor variable on the regressed variable. Both concepts can be captured using the following linear expression:

$$Y_i = a_0 + a_1X_1 + a_2X_2 + \cdots + a_kX_k + U_i \quad (1)$$

where Y_i represents the explained variable and $X_1, X_2, \ldots, X_k$ las k the possible explanatory variables. The coefficients a represent a measure of the effect that a change in each independent variable has on the dependent variable. Separately, U_i is the stochastic error term, which encompasses all disturbances not caused by the regressor variables.
To verify whether the variables $X_1, X_2, \ldots, X_k$, each have a statistically significant individual effect on Y_i hypothesis tests are formulated for each one, following the structure below:

$$H_0: a_j = 0 \quad \text{vs} \quad H_a: a_j \neq 0, \text{ para } j = 1,2, \ldots, k$$

To test the hypotheses, p-values are used. A p-value lower than 0.05 indicates that the variable X_j is statistically significant in explaining changes in Y_i, at a 95% confidence level. The distribution used for these tests is the student's t-distribution. The probability values will hereafter be referred to as P_{value}.

A linear regression analysis was chosen not because the independent variables are assumed to have a linear functional relationship with the dependent variable, but rather because the priority was to obtain easily interpretable coefficients.

Results

Initially, the objective was to identify a series of significant factors influencing the number of fentanyl overdose deaths in the population of the United States of America. Therefore, the following model was proposed:

$$Y_i = a_0 + a_1X_1 + a_2X_2 + a_3X_3 + U_i \quad (2)$$

Equation (2) illustrates that some of the most relevant factors influencing the level of fentanyl addiction deaths are per capita health expenditure, the percentage of the population in the 15 to 34 age group, and the unemployment rate. A linear regression model was applied to the collected data (Appendix 1). The descriptive statistics corresponding to these data are presented in Appendix 3.

The resulting estimate is:

$$\widehat{Y_i} = 86.783 + 27.359X_1 - 3.445X_2 + 6.620X_3 + U_i \quad (3)$$

P_{value} (0.0001) (0.0107) (0.0006)

Mathematical expression (3) shows the three factors statistically significant at a 95% confidence level on the levels of fentanyl abuse at the state level (measured as the fatal overdose rate per 100,000 inhabitants).

Regarding per capita health expenditure (X_1), intuitively, estimate (3) shows that if a state spends 1,000 dollars more per capita on public medical services, the number of deaths per 100,000 inhabitants increases by 27. In other words, in a population of 100,000 inhabitants, if per capita spending increases by one thousand dollars, there will tend to be, on average, 27 more fentanyl overdose deaths. This seemingly paradoxical result is explained in the subsequent discussion section.

Concerning the percentage share of the population aged 15 to 34, expression (3) indicates that for each percentage point increase in the population within this age group, 3 fewer fentanyl overdose deaths per 100,000 inhabitants will be recorded in a given state. This suggests the involvement of social factors (see discussion).

The third and final variable found to be statistically significant was the unemployment rate (see P_{value} of 0.0006), showing intuitively that for each percentage point increase in the unemployment rate, there will be 6 more deaths per 100,000 inhabitants in a given state. This supports the notion that an unemployed person may feel hopeless and have time to resort to drug use as a form of "relief."

Finally, there might appear to be a correlation between the variables for the percentage of the population aged 15 to 34 and unemployment; however, this is not the case, as shown in the following expression:

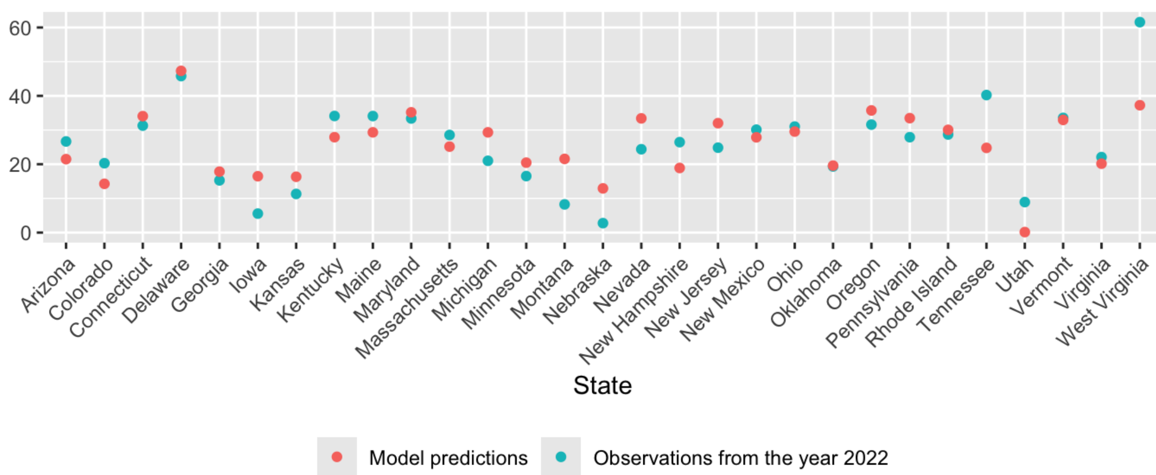
$$\widehat{X_3} = 6.24 - 0.10X_2 \qquad (4)$$

$$P_{value} \qquad (0.289)$$

This correlation was not used at all due to its lack of significance. Based on expression (3), two relevant conclusions were drawn: first, that employed individuals tend to avoid fentanyl use, and second, that people aged between 15 and 34 are not the group most prone to addiction to this drug. For expression (3), it is worth noting that the reported p-values were calculated using a statistical correction for error autocorrelation, known as Newey-West robust standard errors.

The assumption tests corresponding to equation (3) are presented in Appendix 4. Finally, it is pertinent to present a graphical comparison between the estimates produced by the model for each state in the sample (by substituting the independent variables in expression (3)) and the actual observations for the year 2022. In Figure 1, the estimated number of deaths obtained by applying the model to the independent variables of 2022 is shown in green, while the real data for the number of deaths per state in the same period are illustrated in red. The data shown in this graph are also presented in tabular form in Appendix 2.

Figure 1
Comparison of the model´s results and actual data from the year 2022



Source: Author's own work

Discussion

Three factors were found to be significant among all the variables included: per capita public health expenditure, the proportion of the population aged 15 to 34, and the unemployment rate. Regarding health expenditures, a positive correlation was found with the number of fentanyl overdose deaths. This phenomenon could be due to the demographic characteristics of territories that allocate a considerable portion of their government budget to healthcare needs—a third explanatory factor. Jurisdictions with substantial healthcare budgets tend to have populations suffering from chronic illnesses, which, as Wu et al. (2018) point out, predispose individuals to addiction disorders.

This correlation between other ailments and addiction could also have an economic explanation. In the United States, medical debt has become a significant economic and social problem. An estimated 17.8% of the U.S. population has incurred debt to pay for medical services (Mahoney et al., 2021). Such financial obligations act as a major psychological stressor for the affected population (Wiltshire et al., 2020). These and similar stressors are risk factors for addiction (Sinha, 2009). Additionally, being in medical debt limits an individual's access to adequate treatment, making them more prone to overdose (Moon et al., 2024). The conclusions of these authors could support the correlation found in the current analysis.

Regarding the proportion of the population aged 15 to 34, a negative correlation was found between this figure and the level of fentanyl overdose deaths at the state level. This could be due to social and cultural factors specific to the studied sample that emerged during the COVID-19 pandemic. The 2022 edition of the Monitoring the Future survey, conducted by the University of Michigan on a representative sample of American adolescents, recorded historically low levels of drug use in its target population. According to Miech et al. (2022), these statistics may be explained by the social nature of illegal substance use among youth. The authors note that, with this group isolated during the recent SARS-COV2 pandemic, their mutual interactions decreased, leading to a reduced tendency toward drug addiction.

Changes in preferences due to social environmental influence have been modeled economically. Pollak (1976) proposed the model of interdependent preferences, where an individual's decisions depend on those of their social group. Shah and Asghar (2023) complement this theoretical framework, stating that utility functions within individuals of a community tend to converge, especially regarding goods providing immediate gratification. Makgosa and Mohube (2007) further note that peers are one of the most relevant social influences on youth. The lack of socialization and isolation caused a widespread change in the preferences and consumption attitudes of North American youth regarding drugs, aligning with Basman's (1956) proposition that demand can be time-varying and dependent on consumer preferences. These theoretical frameworks may justify the negative slope found between the percentage of the population aged 15 to 34 and fentanyl-related death rates in expression (3).

On the other hand, the observed relationship between the unemployment rate and fentanyl overdose death rates also has an explanation in existing economic literature. This phenomenon fits the model proposed by Ainslie (1975), which posits that addiction is inversely related to the difficulty of accessing the addictive substance and directly related to the difficulty of obtaining substitutive rewards, such as professional development and employment. This implies that individuals engaged in the labor market are less susceptible to the hyperbolic discounting cases proposed by Harris and Laibson (2012) and are more inclined to prioritize future utility over the immediate gratification provided by addictive substances. Said authors provide a theoretical explanation for the coefficient obtained between the unemployment rate and fentanyl deaths in equation (3).

Regarding variables found not to be significant (see Data and Methods), their influence on the dependent variable may not have been evident due to the study's relatively short timeframe and the lack of consideration for changes across multiple years. It is possible that the impact of these factors relates to structural economic changes whose repercussions cannot be adequately quantified using data from only one year. Finally, it is necessary to consider the underreporting of fentanyl overdose deaths due to the nature of the phenomenon, which could bias some of the calculations.

Conclusions

A linear regression analysis was conducted with the objective of identifying correlations between various socioeconomic factors and the number of fentanyl overdose deaths across different U.S. states, using the latter as the dependent variable. Overall, the results indicate that economic and demographic characteristics significantly influence the level of fatalities due to fentanyl use.

Most notably, the unemployment rate was found to exert a positive effect on the number of deaths. It can be estimated that for every one-percentage-point increase in the unemployment rate in a given state, there are approximately six additional deaths per 100,000 inhabitants in that region. This observed relationship between unemployment and the dependent variable may be explained by the notion that being part of the labor force provides individuals with an alternative source of reward, thereby reducing the likelihood of substance use.

The findings also suggest that unemployment is a key variable influencing fentanyl addiction levels. Therefore, an effective public policy aimed at combating the epidemic could focus on promoting adequate job placement. Additionally, the correlation between the proportion of the population aged 15 to 34 and the dependent variable was found to be negative. This phenomenon may be explained by changes in the interdependent preferences of American youth.

The factors identified in this study complement the previous literature (see Literature Review), which has primarily focused on educational, law enforcement, wealth, and social inequality dimensions as causes of the opioid crisis. This analysis contributes a distinct perspective by placing greater emphasis on the role of unemployment.

Finally, it is important to acknowledge certain limitations of this study. The analysis is based on data from a single year, which restricts the ability to examine the evolution of the

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identified relationships over time. Furthermore, a linear regression model was employed, which limits the ability to capture non-linear relationships between the variables.

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Appendix 1: Data compiled for the linear regression (3)

State	Y_i	X_1	X_2	
Arizona	26.658	0.143	27.4	3.8
Colorado	20.291	0.238	28.9	3.1
Connecticut	31.290	0.366	26.1	4.1
Delaware	45.791	0.676	25.1	4.3
Georgia	15.276	0.217	27.7	3.1
Iowa	5.550	0.114	26.7	2.8
Kansas	11.308	0.270	27.6	2.6
Kentucky	34.111	0.191	26.3	4
Maine	34.090	0.181	23.5	2.8
Maryland	33.383	0.661	26	3
Massachusetts	28.550	0.352	27.8	3.7
Michigan	20.998	0.244	26.5	4.1
Minnesota	16.522	0.245	26.2	2.6
Montana	8.242	0.223	25.9	2.7
Nebraska	2.756	0.180	27.1	2.2
Nevada	24.381	0.140	26.6	5.2
New Hampshire	26.456	0.147	25.3	2.3
New Jersey	24.834	0.252	25.4	3.9
New Mexico	30.107	0.241	26.9	4.1
Ohio	31.015	0.239	26.2	4
Oklahoma	19.342	0.281	27.7	3.1
Oregon	31.588	0.526	26.5	3.9
Pennsylvania	27.907	0.320	25.9	4.1
Rhode Island	28.695	0.665	27.9	3.2
Tennessee	40.238	0.285	26.8	3.4
Utah	8.922	0.193	31.3	2.4
Vermont	33.549	0.724	25.8	2.3
Virginia	22.076	0.274	26.9	2.8
West Virginia	61.573	0.318	24.4	3.9

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Appendix 2: Comparison between actual observation and predictions obtained from the model.

State	Data point:2022	Prediction
Arizona	26.658	21.484
Colorado	20.292	14.268
Connecticut	31.291	34.057
Delaware	45.791	47.310
Georgia	15.277	17.832
Iowa	5.551	16.479
Kansas	11.308	16.332
Kentucky	34.111	27.909
Maine	34.091	29.326
Maryland	33.384	35.182
Massachusetts	28.550	25.152
Michigan	20.998	29.325
Minnesota	16.522	20.459
Montana	8.243	21.557
Nebraska	2.757	12.928
Nevada	24.381	33.413
New Hampshire	26.457	18.902
New Jersey	24.835	32.007
New Mexico	30.107	27.871
Ohio	31.016	29.554
Oklahoma	19.343	19.597
Oregon	31.589	35.731
Pennsylvania	27.908	33.478
Rhode Island	28.695	30.056
Tennessee	40.238	24.777
Utah	8.923	0.144
Vermont	33.550	32.964
Virginia	22.077	20.158
West Virginia	61.574	37.261

Appendix 3: Descriptive statistics table.

Variable	Y_i	X_1	X_2	X_3
Mean	25.7074	0.3076	26.6345	3.3621
Median	26.6582	0.2454	26.5000	3.2000
Standard deviation	12.4310	0.1729	1.4331	0.7528
First quartile	17.9325	0.1925	25.9000	2.7500
Third quartile	32.4861	0.3364	27.5000	4.0000
IQR	14.5536	0.1439	1.6000	1.2500

Appendix 3: Assumption tests for the regression model (3)

Assumption	**Statistical test applied**	**Value considered**	**Criterion applied (at 95% significance level)**
The model is correctly specified.	RESET test (considering the correct model specification as the null hypothesis)	P_{value} 0.496	The model is correctly specified.
Homoscedasticity of the errors	Breusch- Pagan test (considering homoscedasticity of the errors as the null hypothesis)	P_{value} 0.3979	The residuals are homocedastic.
The errors are normally distributed	Kolmogorov-Smirnov test (considering normality of the errors as the null hypothesis)	P_{value} 0.9754	The residuals are normally distributed.
The errors are not autocorrelated	Durbin-Watson test (considering independence of the errors as the null hypothesis)	P_{value} 0.028	The residuals present first grade autocorrelation.
Statistical significance of the model	Robust f test (considering the model not being significant as the null hypothesis)	P_{value} 0.00002	The model is statistically significant
No multicollinearity	Variance inflation factor	For X_1: 1.0194 ForX_2: 1.0640 For X_3: 1.0444	There is multicollinearity.
Exogeneity	Correlation coefficient between each of the independent variables and the residuals.	For X_1: -0.000000000006 For X_2: 0.000000000000008 For X_3: 0	All of the independent variables are exogenous.

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