Opioid Crisis and Firm Downside Tail Risks: Evidence from the Options Market[†]

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Abstract

This paper explores how the opioid crisis exposure affects firm downside tail risks implied from equity options. Using a large sample of U.S. public firms from 1999 to 2020, we find that firms headquartered in regions with higher opioid death rates face higher downside tail risks, i.e., the cost of option protection against left tail risks is higher. The effects are reversed following exogenous anti-opioid legislations, supporting a causal interpretation. Further analysis shows that the opioid crisis heightens firm risk by reducing labor productivity. The effects that occur through a labor channel are stronger for firms with higher labor intensity, lower labor supply, and lower workplace safety.

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Abstract

This paper explores how the opioid crisis exposure affects firm downside tail risks implied from equity options. Using a large sample of U.S. public firms from 1999 to 2020, we find that firms headquartered in regions with higher opioid death rates face higher downside tail risks, i.e., the cost of option protection against left tail risks is higher. The effects are reversed following exogenous anti-opioid legislations, supporting a causal interpretation. Further analysis shows that the opioid crisis heightens firm risk by reducing labor productivity. The effects that occur through a labor channel are stronger for firms with higher labor intensity, lower labor supply, and lower workplace safety.

Keywords: Opioid Crisis, Labor Risk, Tail Risk, Option Price

JEL Classification: G12, E24, J24, I10

1. Introduction

The opioid crisis refers to a widespread public health emergency characterized by the misuse, addiction, and overdose deaths associated with opioid drugs.[1] It originated from the overprescribing and widespread use of opioids in the late 1990s and early 2000s. Alpert, Evans, Lieber, and Powell (2022) state that overdose deaths involving opioids have experienced a significant increase since the 1990s, resulting in the most severe drug overdose epidemic in the history of the United States. The crisis escalated rapidly, with alarming rates of opioid-related overdoses and deaths. According to the latest information from the National Institute on Drug Abuse (NIDA) and Centers for Disease Control and Prevention (CDC), opioids are the primary driver of drug overdose deaths, which involve 81,806 overdose deaths (75.79% of all drug-involved overdose deaths) in 2022.[2] The crisis has affected individuals from all walks of life, regardless of age, gender, or socioeconomic status. As we showed in Figure 1, the opioid crisis has covered almost all counties in the U.S. in 2020. In addition to the deaths caused by the opioid crisis, it also imposes significant economic costs. For example, the Council of Economic Advisers (CEA) estimates that the economic costs of the opioid crisis are $504 billion, about 2.8 percent of GDP in 2015.[3] Luo, Li, and Florence (2021) show that the economic costs of opioid-related overdose are $1,021 billion in 2017.[4] Using a methodology developed by researchers at the CDC, the U.S. Congress Joint Economic Committee (JEC) estimates that the economic toll of the opioid crisis in the U.S. is nearly $1.5 trillion in 2020—up 37% from

[1] According to the National Institute on Drug Abuse (NIDA), a federal scientific research institute and the world's largest funder of biomedical research on drug use and addiction, opioids are a class of drugs that include the illegal drug heroin, synthetic opioids such as fentanyl, and pain relievers available legally by prescription, such as oxycodone, hydrocodone, codeine, morphine, and many others.

[2] https://nida.nih.gov/research-topics/trends-statistics/overdose-death-rates

[3] https://trumpwhitehouse.archives.gov/briefings-statements/cea-report-underestimated-cost-opioid-crisis.

[4] The economic costs encompass both the costs associated with opioid use disorder and fatal opioid overdoses, including expenses for healthcare, substance use treatment, criminal justice, lost productivity, reduced quality of life, and the value of statistical life lost.

2017 when the CDC last measured the cost.[5] Overall, the economic costs associated with opioid-related overdoses have escalated to a critical level, indicating a crisis situation. The impact of the opioid crisis extends beyond economic costs and encompasses labor market disruptions and public finance challenges.

With the opioid crisis garnering attention, some impacts of the opioid crisis have been examined, among which one important aspect is labor productivity (Ouimet, Simintzi, and Ye (2024)). However, little is known about whether and how the potential adverse impact of the opioid crisis on labor productivity will eventually affect the probability of extremely negative outcomes, which can severely impact a firm's financial health, operations, and overall sustainability. This paper aims to investigate this question by focusing on downside tail risks implied from the option market. Specifically, we will explore whether and how firms' downside tail risks driven by the opioid crisis are priced in the option market, meaning whether firms exposed to a higher level of opioid crisis risks exhibit a higher cost of option protection against downside tail risk.[6]

Why firm's exposure to the opioid crisis will affect its downside tail risk? The opioid crisis will exert an adverse influence on firms' workforce and productivity by compromising employee health (Ouimet, Simintzi, and Ye (2024)). For example, employees affected by opioid addiction often exhibit higher rates of absenteeism (missing work) and presenteeism (being at work but not functioning effectively). This reduces overall productivity as these workers contribute less effectively to the firm's output. A large decrease in a firm's output will eventually lead to a higher probability of negative outcomes, or higher downside tail risks. However, the degree to which opioid crisis risk will affect individual firms remains highly uncertain. We will estimate this effect using the downside tail risk inferred from the option market, which can provide forward-looking

[5] https://www.jec.senate.gov/public/index.cfm/democrats/2022/9/the-economic-toll-of-the-opioid-crisis-reached-nearly-1-5-trillion-in-2020

[6] Following Kelly, Pástor, and Veronesi (2016) and Ilhan, Sautner, and Vilkov (2021), the term "priced" indicates that option prices reflect the higher risk associated with certain stocks compared to others, rather than the market compensating investors for taking on a specific risk through expected returns.

information about perceived uncertainty and risk (Kelly, Pástor, and Veronesi (2016); Ilhan, Sautner, and Vilkov (2021); Cao, Goyal, Xiao, and Zhan (2023)), and the literature has shown that option traders have superior information compared to traders in other markets (Easley, O'Hara, and Srinivas (1998); An, Ang, Bali, and Cakici (2014)).[7]

To measure investors' perceived downside tail risks, we follow Bakshi, Kapadia, and Madan (2003), Kelly, Pástor, and Veronesi (2016), and Ilhan, Sautner, and Vilkov (2021) to employ two tail risk measures derived from the option market. Option-based measures used in this paper are constructed from options with a maturity of 30 days because short-term options have higher trading volumes and lower transaction costs than their long-term counterparts. Consequently, the prices of short-term options are more responsive to investors' information flow and changes in perceived uncertainties and risks. Besides, options have different strike prices, allowing us to examine the cost of protection against downside tail risk. The first measure we use is the negative model-free implied skewness (NMFIS), which quantifies the asymmetry of the risk-neutral distribution of underlying stock returns. A more positive NMFIS value indicates a shift of the probability mass under the risk-neutral measure from the right to the left tail, suggesting a higher cost of option protection against downside tail risk. The second measure is the implied volatility slope (SlopeD), representing the relationship between left-tail implied volatility and moneyness. A more positive value of SlopeD indicates that deeper out-of-the-money (OTM) puts are relatively more expensive, suggesting a relatively higher cost of option protection against downside tail risk. Therefore, higher NMFIS and SlopeD values represent higher perceived downside tail risk.

[7] Many other studies also examine the information advantage of the option, such as Cremers and Weinbaum (2010) and Xing, Zhang, and Zhao (2010). Investors trade in the option market because of the higher embedded leverage; thus, the information may be incorporated into the option market more efficiently. Furthermore, option market participants primarily consist of institutional investors with a heightened risk sensitivity.

Firms' exposure to the opioid crisis is measured by the county-level drug-poisoning death rates of firms' headquarters. Drug-poisoning death rates are a useful proxy for opioid abuse, as 75.36% of overdose deaths in the United States involve opioids (CDC (2021)), and are commonly used in the literature (Jansen (2023), Cornaggia, Hund, Pisciotta, and Ye (2023)). To explore whether the opioid-related downside risk is priced on the option market, we first examine the relationship between firm downside tail risk and its exposure to the opioid crisis. Using a large sample of U.S. public firms from 1999 to 2020, we find that firms in counties with higher drug-poisoning death rates (higher exposures to opioid crisis) are associated with higher downside risk, measured by NMFIS and SlopeD. A one-standard-deviation increase in opioid-related death rate leads to an increase of 0.020 (0.016) in NMFIS (SlopeD), which is approximately 5% of the variables' standard deviation for both NMFIS and SlopeD. The findings validate our initial hypothesis, demonstrating that when firms confront a high degree of the opioid crisis, they experience elevated downside tail risks.

To establish causality and address potential endogeneity issues, we utilize the staggered implementation of state-level Prescription Drug Monitoring Programs (PDMPs) as exogenous shocks to reduce opioid crisis risk (Cornaggia, Hund, Nguyen, and Ye (2022)). PDMPs are state-level electronic databases designed to monitor and track the prescribing and dispensing of controlled substances, with a specific focus on prescription opioids. The primary objective of PDMPs is to encourage responsible usage of prescription drugs, prevent the abuse of prescription medications, and improve patient safety. By providing physicians with access to comprehensive and up-to-date information on patient's prescription history, physicians can reject to give similar prescriptions if they assess that a patient may be prone to opioid abuse, effectively reducing the opioid crisis by minimizing the potential for misuse and abuse of opioids. The empirical finding demonstrates that the implementation of PDMPs can significantly reduce the opioid-related death rate. Our staggered Difference-in-Differences (staggered DID) analysis reveals a decrease in downside tail risk for firms located in regions that have implemented PDMPs. This result lends support to a causal relationship between the opioid crisis and downside tail risk implied from the option market. Furthermore, we use Propensity score matching (PSM) and stacked Difference-in-Differences (stacked DID) methods to address potential bias from the staggered DID method. The results are robust to alternative methods.

To further explore whether the positive relationship between the opioid crisis and downside tail risk is driven by its negative impact on employees, we first test how the opioid crisis affects firm labor productivity. We find that firms headquartered in regions with higher opioid death rates exhibit lower labor productivity and tend to recruit more employees in the following year. We then conduct several cross-sectional heterogeneity tests regarding labor intensity, labor supply, and workplace safety. Firstly, firms in labor-intensive industries are particularly vulnerable to the opioid crisis because these industries heavily rely on labor productivity. Thus, among these industries, absenteeism and presenteeism caused by the opioid crisis will reduce overall productivity to a larger degree, and we expect the effects to be more pronounced for firms in the high labor-intensity industry. To explore this possibility, we classify the mining industry, construction industry, and manufacturing industry as labor-intensive industries, and we find the negative impact of the opioid crisis on downside tail risks is significantly stronger in these industries.

Secondly, though the opioid crisis would negatively affect employees' productivity, the impact could be mitigated if the firm could easily find alternative employees to replace the addicted ones. Therefore, firms located in the region with a higher labor supply can help firms replace less productive employees more easily, which can potentially reduce the negative impact of the opioid crisis on labor productivity. As a result, we hypothesize that the effects should be more pronounced for firms with a lower labor supply. To investigate this channel, we divide all the firms every year into two groups based on the labor force rate, which is a proxy for labor supply and measured as the ratio of the labor force over the total population of each county, and then repeat our baseline analysis in two subgroups. Consistent with the conjecture, we find that the impact of the opioid crisis on firm downside tail risks is more pronounced for firms with lower local labor supply.

As a third channel, we conjecture that workplace safety would also affect the relationship between the opioid crisis and firm downside tail risks. All else equal, firms with better workplace safety could identify potential hazards, prevent accidents and injuries, and thus promote a safe working environment, through different methods like introducing training and education, health and wellness, drug-testing programs, etc. Consequently, the adverse effects of the opioid crisis on employees could be mitigated, and we expect our results to be less significant among firms with higher workplace safety. Using the occurrence of incidents related to workplace safety as a proxy, we find supporting evidence consistent with our conjecture.

In summary, the channel tests show that the effects of the opioid crisis on firm downside tail risk are driven by its adverse impact on employee productivity, and our results are more pronounced for firms with higher labor intensity, lower labor supply, and lower workplace safety.

We also conduct some further discussions and several robustness tests. First, we rule out the potential impact of the local economy on the relationship between the opioid crisis and downside tail risks, by showing the results do not differ in counties with high GDP growth and low GDP growth. Second, in our baseline results, we measure firm-level opioid risk using the opioid death rate of the firm's headquarters county. Since the firm's operations may not be concentrated in its headquarters, we use the firm's establishment-level data and construct the firm-level opioid risk measure using the weighted opioid risk measure from its various establishments. Thirdly, we also conduct the baseline regression using several alternative measures for opioid-related death rate, and the results hold. Fourthly, we do the placebo test to confirm our findings are not driven by other death reasons. Lastly, we find that the effect of the opioid crisis on firm tail risk is much stronger in states with higher investor attention to opioid risk. Overall, these robustness tests strengthen the validity of our baseline results and provide additional confidence in the relationship between the opioid crisis and downside tail risk derived from the option market.

Our paper contributes to three strands of literature. First, this paper is related to the research on the effects of the opioid crisis. Previous studies have documented the negative impact of the opioid crisis on local economic conditions, such as increased municipal borrowing costs (Cornaggia et al. (2022)), reduced deposit growth and mortgage lending (Li and Ye (2022)), spillover effects on consumer finance (Jansen (2023)), lower labor force participation rate in labor markets (Krueger (2017); Park and Powell (2021); Aliprantis, Fee, and Schweitzer (2023)), and declined real estate price (D'Lima and Thibodeau (2023)). Besides, studies have shown that the opioid crisis negatively affects firm outcomes, including reduced firm innovation (Cornaggia et al. (2023)) and decreased firm growth and investment (Ouimet, Simintzi, and Ye (2024)). Our paper is the first to focus on the relationship between the opioid crisis and investor-perceived downside tail risk implied from the options market.

Furthermore, this paper contributes to the human capital literature on the effect of employees on firms' risk or performance. Martin (2021) demonstrates a positive relationship between employee training and firm performance. Au, Dong, and Tremblay (2021) show that employee flexibility increases firm value. Li, Lourie, Nekrasov, and Shevlin (2022) find a positive relation between employee turnover and the uncertainty of firm future performance. Rettl, Schandlbauer, and Trandafir (2024) find that employee health risk negatively affects firm performance. Existing literature shows labor is an important driver of firm fundamentals. Our paper is the first to examine how investors respond to human capital risks stemming from the opioid crisis and how these risks are priced in the option market.

This paper is also linked to the literature on how firm risk affects the option market. Theoretically, Pástor and Veronesi (2013) show that political uncertainty erodes the value of the implicit put protection offered by the government to the market. Dubinsky, Johannes, Kaeck, and Seeger (2019) find that earnings announcement risks can be priced in the option market. Kelly, Pástor, and Veronesi (2016) find that options for those whose lives span political events tend to be more expensive, reflecting that political uncertainty is priced in the options market. Empirically, Ilhan, Sautner, and Vilkov (2021) find that the cost of protection against downside tail risks is higher for firms with more carbon-intensive business models. Cao, Goyal, Zhan, and Zhang (2023) find that ESG-related uncertainty is priced in the option market. Our study focuses on the firm uncertainty related to opioid crisis risk and shows that the risk associated with human capital, one of the most important assets of the firm, is priced in the option market.

The rest of the paper is organized as follows. Section 2 describes the data and measures construction. Section 3 presents our baseline results. Section 4 analyzes the underlying channels. Section 5 shows robustness tests and further discussion. Section 6 concludes.

2. Data and Measures

We collect the opioid crisis data from the Centers for Disease Control and Prevention (CDC) WONDER Online Database from 1999 to 2020. We obtain data from both option and stock markets for U.S. public firms. Specifically, data on U.S. individual stock options are sourced from OptionMetrics, and stock price and returns data are obtained from the Center for Research in Security Prices (CRSP). Accounting data are collected from Compustat. Furthermore, we access risk-free rates from Kenneth French's website and institutional holdings data from Thomson Reuters (13F). We gather county-level data on population, personal income, and employment from the Bureau of Economic Analysis (BEA) and Bureau of Labor Statistics (BLS) websites.

2.1 Opioid crisis

To estimate the impact of the opioid crisis, we measure drug-poisoning death rates at the county level as a proxy for the local level of the opioid crisis risk (the number of drug-poisoning deaths adjusted for county population (per 100,000)). Our data is obtained from the Centers for Disease Control and Prevention (CDC) WONDER Online Database from 1999 to 2020.[8] The CDC WONDER database provides county-level national mortality and population data covering the period from 1999 to 2020. It provides information on both underlying and multiple causes of death, allowing for a detailed analysis of mortality at the county level. Following previous studies (Jansen (2023); Cornaggia et al. (2023)), we identify drug-related death to proxy for opioid-related death using underlying International Classification of Diseases, 10th Revision (ICD-10) codes, including X40-X44 (accidental poisonings by drugs), X60-X64 (intentional self-poisoning by drugs), X85 (assault by drug poisoning), and Y10-Y14 (drug poisoning of undetermined intent). It is worth noting that the CDC suppresses the death counts if a county has less than ten deaths in a given year to protect the privacy of individuals. To address this issue, we supplement the suppressed data with county-level drug poisoning mortality rates estimated using Hierarchical Bayesian models provided by the CDC's National Center for Health Statistics (NCHS) from 2003 to 2020.[9]

One limitation of the measure is that it is not a direct measure of the opioid crisis, because drug-related deaths also include deaths resulting from other forms of substance abuse such as cocaine, methamphetamine, and amphetamine. However, we think this is a reasonable substitute, because recent data from the CDC shows that more than 75.36% of overdose deaths involve the use of prescription or nonprescription opioids. Moreover, opioid abuse is difficult to measure, and panel data is not available. Besides, the data will

[8] https://wonder.cdc.gov/mcd-icd10.html or https://wonder.cdc.gov/ucd-icd10.html

[9] The details of estimation procedure could be found here: https://www.cdc.gov/nchs/data-visualization/drug-poisoning-mortality/#techNotes. In robustness test, we further restrict our sample to the counties with more than 10 overdose deaths and all the main results hold.

be suppressed if a county has less than ten deaths in a given year. We can find the estimated drug-related death data to supplement the drug-related deaths, but we cannot find the corresponding estimated data for opioid-related deaths. Therefore, in light of the ready availability of data concerning drug-related deaths and the proportion of opioid-related deaths in drug-related deaths, we choose to use drug-related death data as a substitute for opioid-related death data.

2.2 Downside tail risk measures

The option market contains information about investor expectations, and the information can predict future asset prices (Kelly and Jiang (2014); Bollerslev, Todorov, and Xu (2015)). Besides, various uncertainties are priced in the option market, such as political uncertainty (Kelly, Pástor, and Veronesi (2016)) and climate policy uncertainty (Ilhan, Sautner, and Vilkov (2021)). In this study, we use option-based measures to assess the effects of opioid risk uncertainty. Following Ilhan, Sautner, and Vilkov (2021), we use OTM call and put data with absolute deltas smaller than 0.5 from the Surface File of Ivy DB OptionMetrics and focus on measures derived from options with a maturity period of 30 days. Short-term options have higher trading volumes and lower transaction costs than their long-term counterparts. Consequently, the prices of short-term options are more responsive to investors' information flow and changes in perceived uncertainty and risks.

We construct two option-based measures to identify downside tail risk, including the negative model-free implied skewness (NMFIS) and the implied volatility slope (SlopeD). The first measure is the negative model-free implied skewness (NMFIS), constructed following Bakshi, Kapadia, and Madan (2003) and Ilhan, Sautner, and Vilkov (2021). NMFIS is computed using the standard formula for the skewness coefficient as the third central moment of the risk-neutral distribution normalized by the risk-neutral variance (raised to the power of 3/2), and then taking the negative value. NMFIS at time t for the period τ is constructed as:

$$NMFIS\ t,\tau \ = \ -\frac{e^{r\tau}W(t,\tau) - 3\mu(t,\tau)e^{r\tau}V(t,\tau) + 2\mu(t,\tau)^3}{[e^{r\tau}V(t,\tau) - \mu(t,\tau)^2]^{3/2}} \tag{1}$$

Where $V(t,\tau)$is the price of the volatility contract, $W(t,\tau)$ is the price of the cubic contract, $\mu(t,\tau)$ is the risk-neutral expectation of the underlying log return over the period τ, and r is the risk-free rate (Details see Bakshi, Kapadia, and Madan (2003) and Ilhan, Sautner, and Vilkov (2021)). It quantifies the asymmetry of the risk-neutral distribution, providing information about the relative expensiveness of protection against left-tail events compared to right-tail events. As NMFIS is affected by both left and right tails, a more positive NMFIS value indicates a shift of the probability mass under the risk-neutral measure from the right to the left tail, suggesting a higher cost of option protection against downside tail risk. It also can be interpreted as the cost of protection against left tail events relative to the cost of gaining positive realizations on the right tail.

The second measure is the implied volatility slope (SlopeD), which is constructed following Kelly, Pástor, and Veronesi (2016) and Ilhan, Sautner, and Vilkov (2021). SlopeD is obtained by regressing the implied volatilities of OTM puts with Black-Scholes delta ranging from -0.5 to -0.1 on their corresponding deltas and a constant term. The slope coefficient obtained from this regression is then denoted as SlopeD, representing the relationship between left-tail implied volatility and moneyness. It quantifies the cost of protection against extreme downside tail events relative to the cost of protection for less extreme downside events. A more positive SlopeD value indicates that deeper OTM puts (with smaller absolute deltas) are relatively more expensive, suggesting a higher cost of protection against downside tail risk.

2.3 Summary statistics

To construct our sample, we start with all U.S. public firms in the OptionMetrics from 1999 to 2020, and merge with CRSP and Compustat. We choose 1999 as the starting year in our sample as it is the first year in which CDC data on opioid death rates became available. We use augmented 10-X header data to link county-level opioid death rates according to the location of firms' headquarters. [10, 11] Following Ilhan, Sautner, and Vilkov (2021), control variables include Log(Assets), Dividends/net income, Debt/assets, EBIT/assets, CapEx/assets, Book-to-market, Returns, CAPM beta, Volatility, and Institutional ownership. We also consider county-level variables, including Population level, Per capita income, Population growth, and Employment growth, following Gao, Lee, and Murphy (2020) and Cornaggia et al. (2022). We exclude utility firms (SIC codes 4900-4949) and financial firms (SIC codes 6000-6999) in our analysis. All the variables are winsorized at the 1% and 99% levels.

Summary statistics for the main variables are presented in Table 1. There are 4,502 unique public firms in our sample. We report firm-level variables in Panel A, including Death rate, NMFIS, SlopeD, and firm-level control variables. In Panel B, we report county-level variables, including Death rate and county-level control variables. Detailed variable definitions are provided in Appendix A. For firm-level measures, the mean and standard deviation of the Death rate (per 100,000) are 13.324 and 8.188, respectively. The average NMFIS (SlopeD) for the sample is 0.367 (0.376), with a standard deviation of 0.392 (0.355). Panel C shows the correlations between all firm-level variables. The correlation between NMFIS and SlopeD is 0.547, which is reasonable because both variables capture downside risks but they are not the same.

[Insert Table 1 about here]

Figure 1 shows the county-level heatmap for opioid-related death rates in 2020. We can observe that almost every county suffers from the opioid crisis, indicating its widespread impact across geographic regions, yet the severity and prevalence of the crisis

[10] https://sraf.nd.edu/sec-edgar-data/10-x-header-data/

[11] In the robustness check, we also use the weighted average opioid death rate in counties where the firm's establishments are located. We use employee numbers, and sales volume of each establishment as weights to construct the firm's opioid-related death rate. The results hold.

exhibit significant geographical variations. Furthermore, it is well-documented that the opioid crisis has experienced a rapid increase from 1999 to 2020. Therefore, large cross-sectional and time-series variation of opioid crisis allows use to gain a comprehensive understanding of the relationship between the opioid crisis and downside tail risk implied from the option market.

3. Baseline Results

3.1 Panel regression

In the baseline analysis, we first examine the effects of the opioid crisis on firm downside tail risk.

$$Tail\ risk_{i,t} = \alpha + \beta \times Death\ rate_{i,t} + Controls_{i,c,t-1} + FEs + \varepsilon_{i,t} \tag{2}$$

where $Tail\ risk_{i,t}$ measures downside tail risk for firm i in year t, including NMFIS and SlopeD. The independent variable, Death rate, is the opioid-related death rate for firm i in year t. We control firm-level and county-level variables at year *t-1*, including Log(Assets), Dividends/net income, Debt/assets, EBIT/assets, CapEx/assets, Book-to-market, Returns, CAPM beta, Volatility, and Institutional ownership, Population level, Per capita income, Population growth, and Employment growth. To account for unobserved heterogeneity, we include firm and year-fixed effects in our model and cluster standard errors at the county level. If the local opioid crisis leads to a higher downside tail risk, β should be significantly positive.

Table 2 presents baseline results. The coefficients related to the Death rate are significantly positive across different specifications, suggesting a positive relationship between the opioid crisis and firm downside tail risk.[12] Specifically, in columns (1) and (2), a one-standard-deviation increase in Death rate (8.188) is associated with an increase

[12] As a robustness check, we run a monthly regression using firm-month level MFIS and SlopeD, or a yearly regression using lagged death rate. The results also hold.

of 0.020 in NMFIS and an increase of 0.016 in SlopeD, which is approximately 5% of the variable's standard deviation for both NMFIS and SlopeD.[13] All findings suggest that the opioid crisis exacerbates the downside tail risk proxied by option-implied measures.

[Insert Table 2 about here]

One potential concern is that pharmaceutical firms and hospitals may experience some positive effects from the opioid crisis as they generate revenue from providing drugs or treatments to individuals with opioid-related issues. To examine the robustness of our findings, we exclude firms in the pharmaceutical industry (SIC codes 2830-2839) and hospitals (SIC codes 8060-8069) and repeat the analysis. The results shown in Table B1 of Appendix B remain consistent with the baseline results.[14]

3.2 Identification: Prescription Drug Monitoring Programs

Our baseline results may be subjected to possible endogeneity issues, such as omitted variables like employees' quality and educational background. To establish a causal linkage between the opioid crisis and downside tail risk, we conduct a staggered Difference-in-Differences (staggered DID) test to address potential endogeneity concerns and to provide further evidence on the effects of the opioid crisis on the downside tail risks implied from the option market.

Following Cornaggia et al. (2022), we utilize the staggered implementation of state-level Prescription Drug Monitoring Programs (PDMPs) as exogenous shocks to reduce the opioid-related death rate. PDMPs are state-level electronic databases designed to monitor and track the prescribing and dispensing of controlled substances, with a specific focus on

[13] Ilhan, Sautner, and Vilkov (2021) use a sample of S&P 500 firms and show that a one-standard-deviation increase in a firm's log industry carbon intensity increases SlopeD by 0.014, which is approximately 10% of the variable's standard deviation.
[14] We find there is no effect in the pharmaceutical firms and hospitals because these firms will not only be affected by the negative impact of the opioid crisis on employee productivity but also benefit from opioid crisis.

prescription opioids. The primary objective of PDMPs is to encourage responsible usage of prescription drugs, prevent the abuse of prescription medications, and improve patient safety. By providing physicians with access to comprehensive and up-to-date information on patient's prescription history, physicians can reject to give similar prescriptions if they assess that a patient may be prone to opioid abuse, effectively reducing the opioid crisis by minimizing the potential for misuse and abuse of opioids. Data on state-level implementations of PDMPs are collected from the Prescription Drug Abuse Policy System.[15] Figure 2 presents the specific distribution and timeline of PDMPs across states in the United States. We hypothesize that PDMPs can exogenously reduce opioid abuse, thus reducing firms' downside tail risk.

We use the first date that authorized users can access their state PDMP database, including online access, as the adoption date of PDMPs in each state. Before we run the staggered DID test, the essential assumption underlying our staggered DID model is that the adoption of PDMPs effectively reduces the opioid-related death rate. Previous evidence indicates that PDMPs lead to fewer opioid pills being prescribed (Surratt et al. (2014); Winstanley et al. (2018)) and reduce opioid-related death rates (Cornaggia et al. (2022)). To validate this assumption, we first examine the relationship between the adoption of PDMPs and the opioid death rate in our sample.

$$Death\ rate_{c,t} = \alpha + \beta \times PDMP_{s,t} + Controls_{c,t-1} + FEs + \varepsilon_{c,t} \tag{3}$$

where $PDMP_{s,t}$ is a dummy variable that equals one after the adoption year of PDMP for firm i located in state s.[16] $Controls_{c,t-1}$ are county-level economic fundamental variables, including Population level, Per capita income, Population growth, and Employment growth. To account for unobserved heterogeneity, we include county and

[15] https://pdaps.org/datasets/pdmp-implementation-dates Although the website provided data only up to 2017, we conduct a manual search for states that have missing data and update the dataset up to 2020. Here, we consider the PDMPs that were adopted from 1999 to 2020. PDMPs adopted beyond our sample period are not considered.

16 $PDMP_{s,t}$ also equals to one in the event year.

year-fixed effects in our model and cluster the standard errors at the county level. We restrict the sample to a five-year window, which includes two years before the PDMP, the year of PDMP implementation, and two years after the PDMP. We also remove firms that relocated their headquarters to other states from our sample.[17] In column (1) of Table 3, the coefficient on $PDMP_{s,t}$ is negative and significant. The effect is substantial, with a decrease in Death rate of approximately 0.699 per 100,000, which corresponds to a nearly 6% reduction in Death rate compared to the county-level mean in this sample (0.699/12.530), indicating that the adoption of PDMPs effectively reduces opioid-related death rates.

To further show the parallel trend, we investigate the dynamic effects of PDMP adoption on downside tail risks, and present the results in Figure 3. The coefficients corresponding to the years preceding the event are individually not statistically significant, indicating no observable pre-trends between treatment and control groups. On the other side, the coefficients become statistically significant from the event year, confirming our assumption that the PDMP implementation was largely unforeseen, and the parallel trend assumption holds.

Next, we run the following regression to examine how the implementation of PDMPs affects downside tail risk implied from the option market:

$$Tail\ risk_{i,t} = \alpha + \beta \times PDMP_{s,t} + Controls_{i,c,t-1} + FEs + \varepsilon_{i,t} \tag{4}$$

where $Tail\ risk_{i,t}$ is the downside tail risk, including NMFIS and SlopeD, for firm i in year t. $PDMP_{s,t}$ is a dummy variable that equals one after the adoption year of PDMP for firm i located in state s. Other control variables shown in Table 2 are also included. To account for unobserved heterogeneity, we include firm and year-fixed effects in our model and cluster standard errors at the county level. We restrict the sample to a five-year window, which includes two years before the PDMP, the year of PDMP

17 We removed 7.8% of the firms from the main sample (330/4502).

implementation, and two years after the PDMP. We also remove firms that relocated their headquarters to other states from our sample. If the adoption of PDMPs mitigates the local opioid crisis, leading to a lower downside tail risk, β should be significantly negative.

The results are shown in Table 3 and summary statistics are presented in Table B2. The coefficients on $PDMP_{s,t}$ in columns (2) and (3) are negative and significant at the 1% level, showing that PDMPs mitigate the positive impact of opioid abuse on NMFIS and SlopeD. Specifically, after PDMP adoption, the firms' NMFIS measure decreases by 0.030, and SlopeD exhibits a 0.028 reduction, about 8% and 9% of the variables' standard deviation for NMFIS and SlopeD, respectively. These findings show there is a causal relationship between the opioid crisis and firm downside tail risk.

[Insert Table 3 about here]

As a robustness check, we use the implementation of PDMPs as an instrumental variable (IV) for the opioid crisis to identify the causal impact of the opioid crisis on downside tail risk in the whole sample. The implementation of PDMPs is negatively correlated to opioid deaths (relevance condition) but should not affect the downside tail risk (exclusion restriction). We show the IV results in Table B3. Consistent with staggered DID analysis, we find there is a negative relationship between the implementation of PDMPs and the opioid crisis and a positive relationship between the opioid crisis and downside tail risks.

3.3 Alternative identification methods

In this section, we use the propensity score matching (PSM) method to match firms that experienced the implementation of PDMPs with those that did not, based on key firm characteristics in the year preceding the shock, including Log(Assets), Debt/assets, EBIT/assets, CapEx/assets, Book-to-market, and Institutional ownership. This approach allows us to compare the downside tail risks of treated firms and control firms with similar characteristics, before and after the introduction of PDMPs.[18]

The result in column (1) of Table 4 Panel A again reveals that the implementation of these monitoring programs is associated with a decrease in opioid overdose deaths, suggesting these policies effectively mitigate the opioid crisis. Negative coefficients in columns (2) and (3) show the treated firms that experience PDMPs have lower downside tail risks relative to similar peers, lending further support to the causal relationship between the opioid crisis and firm downside tail risks. In addition, we show no observable pre-existing trends between the treatment and control groups in Figure 4 and confirm that the difference in matching characteristics between treated firms and control firms does not change after the PDMPs in Panel B, Table 4.

[Insert Table 4 about here]

Recent developments in econometric theory have raised concerns about the validity of the two-way fixed effects (TWFE) difference-in-differences (DID) estimator in settings with variations in treatment timing. When using staggered DID methods to estimate static or dynamic treatment effects, significant biases may arise due to staggered treatment timing and treatment effect heterogeneity. To address these issues, we use stacked regression, following Cengiz, Dube, Lindner, and Zipperer (2019) and Baker, Larcker, and Wang (2022). The core idea behind this approach is to construct event-specific datasets, where each event represents a cohort that includes both the treated group and a clean control group that does not experience the shocks. We stack the event-specific datasets together and estimate a TWFE DID regression on the combined dataset, incorporating dataset-specific firm-cohort and time-cohort fixed effects. The settings are consistent with those described in section 3.2. The results presented in Table B4 and Figure B1

[18] We also restrict the sample to a five-year window and exclude firms that relocated their headquarters to other states from the sample.

consistently support our findings in Table 3, indicating a positive association between the opioid crisis and firm downside risk.

4. Underlying Channels

4.1 The effect of opioid crisis on firm labor productivity

The opioid crisis exerts a detrimental impact on employee health, leading to a decline in workforce and productivity within firms (Ouimet, Simintzi, and Ye (2024)). As the opioid epidemic continues to spread, it affects an increasing number of employees who struggle with addiction and related health issues. This, in turn, may result in lower levels of job performance, and increased job recruitment for new employers. In this subsection, we first examine whether firm productivity is impacted by the opioid crisis. Following Flammer (2015), we define labor productivity as the ratio of sales to the number of employees.[19] Table 5 presents the results of our analysis. The coefficient in column (1) is negative and significant, indicating a negative relationship between the opioid crisis and firm labor productivity.[20] Specifically, a one-standard-deviation increase in the death rate (7.602) correlates with a decrease of 10.00 in labor productivity, which represents approximately 2% of the variable's standard deviation.

Moreover, a decrease in firm productivity often prompts firms to increase recruitment in the subsequent year. We measure the number of employees that firms seek to hire as the number of jobs posted by a firm in year *t+1* divided by sales in year *t*. We

[19] Flammer (2015) points out that this variable has a severe distribution of extreme values. Therefore, in this regression, we winsorize the data at the 2.5% and 97.5% levels. Following Flammer (2015), we also winsorize at 5% and 95% levels. and the results remain consistent. For any missing data in the labor productivity variable, we impute the industry mean.

[20] We also run county-level regressions of the unemployment situation on the opioid crisis. The unemployment level is defined as the logarithm of the number of unemployed individuals in each county for each year. The unemployment rate is measured as the county's total number of unemployed individuals divided by the county's total labor force for the year. Our findings indicate that both the number of unemployed individuals and the unemployment rate increase when the opioid crisis becomes more severe, which might point to a lower quality of the available labor force.

obtain job posting data from RavenPack Job Analytics database, which includes accurate job data from LinkUp. The period in this sample covers from 2007 to 2020 due to the limitation of job posting data.[21] Our hypothesis posits that a decline in productivity would lead to a higher demand for new hires. The result in column (2) supports our hypothesis. A one-standard-deviation increase in the death rate (9.693) is associated with an increase of 0.057 in job postings, which is approximately 4% of the variable's standard deviation.

[Insert Table 5 about here]

Furthermore, a high number of computer-related job postings might indicate that a company is looking to replace human labor with computer-based solutions. This trend suggests a strategic shift towards automation to mitigate the effects of labor shortages. If this is true, there would be a positive relation between the opioid crisis and the number of computer-related job postings. We use the number of computer-related positions posted by a firm within the year *t+1* scaled by the sales of year *t* to proxy the Computer job posting. Using RavenPack Job Analytics database, we identify a job as computer-related if the job position is labeled by RavenPack as a computer occupation (SOC code: 15-1200) based on the Standard Occupational Classification (SOC) system from the U.S. Bureau of Labor Statistics. The result in Table 5 shows a positive relation between the opioid crisis and the number of computer-related jobs. In summary, our findings demonstrate that the opioid crisis significantly hampers firm productivity. This decline in productivity subsequently increases the demand for new hiring, as firms attempt to mitigate the negative impact on their workforce.

[21] RavenPack Job Analytics database offers job posting data from to August 2007, collected directly from company websites by LinkUp. As a leading provider of job market data, LinkUp sources information from over 50,000 employers and 200 million job postings. The database provides comprehensive details on job postings, including company identifiers, job titles, position specifics, job descriptions, and required skills. The results remain consistent if the number of jobs is divided by the number of employees.

4.2 Heterogeneity tests

4.2.1 The effect of employee characteristics

In the previous subsection, we show that the opioid crisis affects firm productivity and subsequent hiring decisions, leading to a higher level of firm downside risk. Naturally, we expect the results would be stronger when the firm relies more on the labor productivity. The CDC has reported that this impact is more pronounced for firms in labor-intensive industries, such as mining, construction, and manufacturing, because these industries heavily rely on labor productivity.[22, 23] Several studies also show that the opioid crisis is severe in those industries (Dale, Buckner-Petty, Evanoff, and Gage (2021); Dong, Brooks, Rodman, Rinehart, and Brown (2022)). Thus, they are particularly vulnerable to the opioid crisis, which results in an elevated level of downside tail risk when they are exposed to a high level of opioid risks. Consequently, the cost of option protection against downside tail risk will increase. To explore whether the effects are more pronounced for firms in the high labor intensity industries, we divide the sample into two subsamples based on the industry classification. High labor-intensive industries include the manufacturing industry (SIC codes between 2000 and 3999), the construction industry (SIC codes between 1500 and 1799), and the mining industry (SIC codes between 1000 and 1499). Firms in high labor-intensity industries are classified as "High Labor Intensity" group, while firms in other industries are classified as "Low Labor Intensity" group.

Table 6 presents results that align with our hypothesis. Specifically, in the "High Labor Intensity" group, we observe that a one-unit increase in Death rate corresponds to an approximate 0.31 percentage-point (t-stat 3.87) increase in the NMFIS and a 0.23 percentage-point (t-stat 2.90) increase in the SlopeD. However, the corresponding increase in the "Low Labor Intensity" group is insignificant, both economically and statistically.

[22] https://www.cdc.gov/niosh/mining/researchprogram/projects/project_OpioidAwarenessTrainingResources.html

[23] https://blogs.cdc.gov/niosh-science-blog/2021/09/14/opioids-in-construction

The differences in coefficients between the two groups for both NMFIS and SlopeD are statistically significant. These findings are consistent with our conjecture that labor is one channel that drives our results. In other words, the opioid crisis has a positive impact on downside tail risks through its adverse impact on labor productivity, thus we find firms in high-labor-intensity industries experience a stronger impact from the opioid crisis, due to their higher dependence on labor.

[Insert Table 6 about here]

Besides, according to the CDC, opioid abuse is much more severe for males than females.[24] There has been a substantial disparity between men and women regarding drug overdoses, with males experiencing a significantly higher number of cases than females and being more severely affected.[25] Therefore, we expect our results should be stronger among firms with more male employees. By dividing the samples into two subgroups based on the proportion of male employees and examining the impact of the opioid crisis on downside risks for two subgroups separately, we find a stronger result in the group of firms with a higher proportion of male employees, which are shown in the Appendix Table B6.[26]

[24] https://nida.nih.gov/research-topics/trends-statistics/overdose-death-rates

[25] Silver and Hur (2020) show that males demonstrate a significantly higher tendency to report opioid misuse, as well as the misuse of prescription opioids, primarily driven by the desire to experience pleasurable sensations or achieve a state of euphoria. The National Institute on Drug Abuse (NIDA) also indicates gender disparities in opioid-related deaths, with males being disproportionately affected, experiencing significantly higher death rates than women. From 1999 to 2020, males account for nearly 70% of all opioid overdose deaths. Besides, according to a CDC report by Wilson, Kariisa, Seth, Smith, and Davis (2020), males had a higher likelihood of using opioids and dying from opioid overdose. For example, males who died of opioid overdose account for roughly 69% of deaths in 2017, respectively.

[26] We obtain the "Women Employees" measure from the Refinitiv database, calculated as the number of women employees divided by the total number of company employees.

4.2.2 The effect of labor supply

Though the opioid crisis would negatively affect employees' productivity, the extent of the opioid impact can be mitigated if a firm could easily find alternative employees to replace the addicted ones, when the region has an ample labor supply. Conversely, recruiting unaffected employees becomes more challenging for firms in regions without adequate labor force, creating difficulties in replacing less productive workers. Such firms will experience heightened vulnerability to the opioid crisis, leading to an increased impact of the opioid crisis on downside tail risk. Accordingly, we expect that firms located in the region with higher labor supply can potentially reduce the impact of the opioid crisis by easily hiring new employees to replace less productive employees.

To proxy for the local labor supply, we define the labor force rate as the ratio of the labor force over the total population of each county for each year. The labor force data is obtained from the Bureau of Labor Statistics (BLS) website. Subsequently, each year, we divide the sample into two subsamples based on the labor supply at the county level. Firms located in the county with a labor supply below the median are classified as "Low Labor Supply", while the others are classified as "High Labor Supply". Then we repeat our baseline analysis for two groups, respectively.

The results are presented in Table 7. In the "High Labor Supply" group, we still observe a positive relationship between the opioid death rate and firm downside tail risks. However, the effects are more pronounced in the "Low Labor Supply" group. In this group, a one-unit increase in Death rate leads to a 0.37 percentage-point increase in the NMFIS and a 0.27 percentage-point increase in the SlopeD, significantly at the 1% level. Moreover, the differences in coefficients on Death rate between the "Low Labor Supply" group and the "High Labor Supply" group are significantly positive, with a p-value of 0.000 for both NMFIS and SlopeD. These findings provide evidence that our results exist for counties with low labor supply and high labor supply, while the impact is much stronger for firms located in counties with a smaller labor pool.

[Insert Table 7 about here]

4.2.3 The effect of workplace safety

As we discussed before, the opioid crisis has a detrimental impact on employee health, thus how firms could manage workplace safety also plays an important role. If firms could introduce training and education programs, health and wellness initiatives, and drug-testing protocols to identify potential hazards and promote a safe working environment, they could mitigate the impact of the local opioid crisis on their downside tail risks.

To explore whether the effect of firm downside tail risk is stronger among firms with lower levels of workplace safety, we use the occurrence of employee health and safety incidents in the previous year as a proxy for workplace safety. Specifically, we use the workplace safety incidents, the "Occupational health and safety issues", from risk incidents of the RepRisk database to measure the firms' workplace safety at the firm level. [27] RepRisk is a news-based database that identifies ESG incidents and evaluates ESG (environmental, social, and governance) risks. Firms that experienced employee health and safety incidents in the previous year are classified as "Low Workplace Safety", and the other firms are classified as "High Workplace Safety".[28]

The results reported in Table 8 are consistent with our hypothesis. Regarding the NMFIS and SlopeD variables, we find that the coefficients of Death rate in the "Low Workplace Safety" group are significant and positive. In contrast, the coefficients of Death rate in the "High Workplace Safety" group are not statistically significant. Differences in coefficients between two groups are significant at the 1% level, for both NMFIS and SlopeD. Though the number of observations is limited, the findings indicate that

[27] We also utilize the Accidents Total measure from the Refinitiv database to proxy for workplace safety. We find consistent results, though the data is limited.

[28] The sample period for our analysis begins in 2008 due to the availability of data from RepRisk.

workplace safety is crucial to affect the impact of the opioid crisis on firm downside tail risks, again showing labor is the underlying channel.

[Insert Table 8 about here]

5. Further Discussion and Robustness Tests

5.1 The potential effect of the local economy

The local economy may also influence the impact of the opioid crisis on the firm downside tail risks. When the local economy is negatively affected by the opioid crisis, firms will have lower demand, less and more expensive outside capital, etc. Therefore, we would like to explore the impact of the local economy on the documented results. We use the growth rate of Gross Domestic Product (GDP) per capita as a proxy for the local economic conditions. This measure is calculated by dividing the GDP of a county by its total population in a given year, and then taking the growth rate.[29] Firms are then categorized into "Low GDP Growth" and "High GDP Growth" groups, based on whether the firm is located in a county with a growth rate of GDP per capita below or above the median, respectively.

The results are reported in Table 9. We find that the opioid crisis has a significant impact on the downside tail risk of firms in both the "High GDP Growth" and "Low GDP Growth" groups. Importantly, there are no statistically significant differences in the coefficients between the two groups. This result suggests that the local economic conditions, as proxied by the GDP per capita growth rate, do not have an impact on the relationship between the opioid crisis and firm downside tail risk. This finding helps us rule out the potential confounding influence of local economic conditions in our analysis.

[29] The GDP and population data are obtained from the Bureau of Economic Analysis (BEA). The sample period covers 2002 to 2020, which corresponds to the availability of GDP data.

[Insert Table 9 about here]

5.2 Opioid crisis from the establishment level

In our baseline results, we measure firm-level opioid risk using the opioid death rate of the firm's headquarters county. Since the firm's operations may not be concentrated in its headquarters, we acknowledge that different locations may face varying degrees of the opioid crisis. Thus, we use the firm's establishment-level data and construct the firm-level opioid risk measure using the locations of the firm's establishments.

We construct alternative measures of the opioid-related death rate using the establishment-level data from the YTS database. The Your-Economy Time-Series (YTS) database is an establishment-level database owned by the Business Dynamics Research Consortium (BDRC) at the University of Wisconsin. In recent years, a growing number of studies have used establishment location data from the YTS database to analyze various aspects, such as job opportunities and investment (Ghent (2021); Campello, Gustavo, d'Almeida, and Kankanhalli (2022)). We extract the establishment-level information from the YTS database, including location, employee numbers, and sales volume. Instead of using the firm's headquarters location in the main sample, we compute the weighted average death rate based on the firm's establishment location.

Specifically, we construct two alternative measures. Death rate EW is calculated as the weighted average death rate for each firm based on the proportion of employees in each establishment. Death rate SW is computed as each firm's weighted average death rate based on its proportion of sales volume in each establishment. Following Ouimet, Simintzi, and Ye (2024), we exclude establishments with fewer than 20 employees from our sample, ensuring that our results are driven by economically significant establishments. The measures constructed using establishment-level data provide a more comprehensive understanding of the firm's overall exposure to opioid crisis risk. As shown in Table 10, the results are largely consistent.[30] Specifically, a one-standard-deviation increase in Death rate EW is associated with a 0.023 increase in NMFIS and a 0.016 increase in SlopeD. This corresponds to approximately 5% of the standard deviation for the NMFIS variable and 4% of the standard deviation for the SlopeD variable. Similarly, a one-standard-deviation increase in Death rate SW is associated with a 0.025 increase in NMFIS and a 0.018 increase in SlopeD, which is around 6% of the standard deviation for NMFIS and 5% of the standard deviation for SlopeD. All the results strengthen the validity and reliability of our findings, lending further support to the conclusions drawn from the analysis.

[Insert Table 10 about here]

5.3 Alternative measures for the opioid crisis

To ensure the robustness and validity of our main results, we conduct several robustness tests to confirm the relationship between the opioid crisis and firm tail risk implied from the option market. In our main sample, we use drug-poisoning death rate from the CDC, with more than ten deaths in a county in a given year, and supplement the suppressed data with county-level drug-poisoning mortality rates estimated by the CDC to proxy for the opioid death rate. We restrict opioid-related death to the underlying ICD-10 code, including X40-X44 (accidental poisonings by drugs), X60-X64 (intentional self-poisoning by drugs), X85 (assault by drug poisoning), and Y10-Y14 (drug poisoning of undetermined intent).

As the first alternative measure (Death rate robust1), we use the death rate directly obtained from the CDC WONDER database for the opioid death rate. The data is not supplemented by estimated drug poisoning death rates calculated by the CDC. Secondly,

[30] The results still hold if we construct the death rate using equal weights instead of weighted averages. We also use the entire sample that does not restrict the employee number to conduct the robustness test and obtain similar results.

following Cornaggia et al. (2022), we narrow the opioid-related death by using the CDC ICD-10 multiple cause codes: natural and semi-synthetic opioids (T40.2), methadone (T40.3), other synthetic opioids (other than methadone) (T40.4), and heroin (T40.1).[31] We do not use the estimated drug poisoning death rates to supplement the suppressed data because the estimated drug poisoning death rates are calculated for drug-related deaths rather than the death with the narrowed reason. We define this measure as Death rate robust2.

From Table 11, we can observe that the results hold for both alternative measures. The coefficients of the alternative death rate measures are significantly positive for NMFIS and SlopeD. The magnitudes of the changes, especially when expressed as percentages of standard deviation, closely resemble the magnitudes observed in the main sample. This finding shows the robustness of our results.

[Insert Table 11 about here]

We also construct other alternative measures. Firstly, we restrict people to working-aged adults (aged 25–64 years) and restrict deaths to more than ten opioid-related deaths. [32, 33] Second, we calculate the opioid-related death rate by dividing drug-related deaths by the county labor force (per 100,000). Thirdly, we exclude deaths related to intentional self-poisoning by drugs (ICD-10 codes: X60-X64). All results are robust and presented in Appendix Table B7.

[31] https://nida.nih.gov/research-topics/trends-statistics/overdose-death-rates

[32] According to the Centers for Disease Control and Prevention (CDC) and the Federal Reserve Economic Data (FRED), individuals between the ages of 25 and 64 are considered working-age adults. https://fred.stlouisfed.org/series/LFWA25TTUSM647N and https://www.cdc.gov/mmwr/volumes/70/wr/mm7048a2.htm

[33] We do not use this specific age group (25 to 64) as our primary sample for two reasons. First, individuals with the age below 25 or above 64 in the United States can still be actively engaged in the workforce. Secondly, we encountered challenges in finding supplementary data to compensate for any suppressed or unavailable information within this particular age range.

5.4 Placebo test: Other death reasons

To ensure that our findings are not influenced by other causes of death, we conduct placebo tests to investigate whether deaths from reasons other than opioid abuse affect firm downside tail risks. This analysis is essential to demonstrate that the observed effects are specifically attributable to opioid-related deaths, rather than being confounded by other mortality factors. We begin by individually examining deaths from all causes, the top three causes of death (heart disease, cancer, and accidents), and the leading cause of death (heart disease).[34] Specifically, we define the following variables for our analysis: All death rate, which represents the death rate from all causes; TOP3 death rate, which includes deaths from the top three causes (heart disease, cancer, and accidents); and TOP1 death rate, which pertains to deaths from the leading cause, heart disease.

The results, presented in Table 12, show that the coefficients for these variables are statistically insignificant. This indicates that deaths from other causes do not significantly affect firm downside tail risks, underscoring the specificity of the opioid risk impact on firm risk. The absence of significant effects from other mortality-related factors reinforces our conclusion that the increase in firm downside tail risks is uniquely driven by opioid-related deaths.[35]

[Insert Table 12 about here]

[34] https://www.cdc.gov/nchs/fastats/leading-causes-of-death.htm Heart disease death is identified using ICD-10 death codes, including I00–I09, I11, I13, and I20–I51. Cancer death is identified using ICD-10 death codes, including C00–C97. Accidents (unintentional injuries) death is identified using ICD-10 death codes, including V01-X59 and Y85-Y86.

[35] We also control for these variables in the main regression to conduct a robustness test. Our findings reveal that the coefficient on opioid deaths remains positively significant, while the coefficients on other death variables are insignificant. These results demonstrate that our findings are not confounded by other causes of death. The adverse impact of opioid death rates on downside tail risks remains robust.

5.5 The effect of investor attention

In this section, we explore the role of investor attention. How opioid crisis risk will be priced in the option market depends on how investors perceive such risk. When investor attention is high, investors become more aware of the extent of the economic effects of the local opioid crisis and are more concerned about the associated uncertainty and risks. Investors who perceive a greater level of risk are willing to pay a higher premium for options that protect against downside tail risk. This increased cost of option protection reflects investors' response to the perceived risks associated with the opioid crisis and their desire to mitigate potential losses. As a result, when the attention to the opioid crisis is higher, the results should be strengthened.

To proxy for the level of investor attention towards the opioid crisis, we use the state-year-level growth rate of SVI from Google Trends for the "opioid epidemic" topic, including the keywords "opioid", "opioid crisis", and "opioid epidemic", among many others. Prior studies have shown that Google's search volume index (SVI) can proxy for investor attention (Da, Engelberg, and Gao (2011)). The index measures search volumes and ranges from 0 to 100. A higher score means higher search intensity, indicating greater investor attention.[36] Each year, we divide all the states into two groups based on the growth rate of SVI. Firms headquartered in the states with investor attention above the median are categorized as "High Investor Attention", while other firms are categorized as "Low Investor Attention". We expect that the effect of the opioid crisis on firm downside tail risk will be more pronounced in the "High Investor Attention" group.

We show the results in Table 13. For NMFIS, compared with the "Low Attention" group, the coefficient of Death rate in the "High Investor Attention" group is more significant and positive (0.0027). The difference in coefficients between the two groups is significant. Similarly, for SlopeD, compared with the "Low Investor Attention" group, the

[36] The sample period for our analysis begins in 2004 due to the availability of data from Google Trends, which provides data starting from 2004. We also use the year-level total search volume, and the results hold.

coefficient of Death rate in the "High Investor Attention" group is more significant and positive (0.0021).[37] Therefore, the results show that the effect of the opioid crisis on firm tail risk is much stronger in states with higher investor attention to opioid risk.

[Insert Table 13 about here]

6. Conclusion

While several studies have examined the impact of the opioid crisis, our study represents a pioneering effort to explore the relationship between the opioid crisis and firm downside tail risk implied from the option market. By utilizing the opioid crisis as an example that negatively affects labor productivity, we provide valuable insights into a more broad question, how the human capital, which is the most important asset of the firm, influences firm fundamentals.

Analyzing U.S. public firms from 1999 to 2020, we establish a positive association between firms' opioid crisis risk and downside tail risk. To address potential endogeneity concerns, we leverage the staggered implementation of state-level Prescription Drug Monitoring Programs (PDMPs) as exogenous shocks to reduce the opioid crisis. By utilizing different econometric settings including staggered DID, PSM-DID, and stacked DID, we establish a causal relationship between the opioid crisis and firm downside tail risk.

Moreover, our study additionally explores the labor channel that contributes to the effect of the opioid crisis risk on firm downside tail risk. We find that the opioid crisis negatively affects firm labor productivity, and firms characterized by higher labor intensity, lower labor supply, and lower workplace safety experience an elevated impact from the opioid crisis on downside tail risk. These findings underscore the importance of

[37] Although the difference in coefficients between the two groups may not be statistically significant, we still observe that the effect is more concentrated within the "High Attention" group.

considering these characteristics when assessing the cost of risk management strategies in the context of the opioid crisis.

Overall, our paper contributes to a more comprehensive understanding of the impacts of the opioid crisis on firm tail risks. Our findings shed light on the previously unexplored relationship between the opioid crisis and firm tail risk implied by the option market, providing valuable insights for academia, practitioners, and policymakers. Future research can expand on these results by investigating further aspects of the opioid crisis's influence on financial markets and risk management strategies.

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Figure 1. County-level heatmap for the opioid crisis

This figure presents an overview of the opioid crisis in 2020. Death rate represents the number of opioid-related deaths, adjusted for county population (per 100,000).

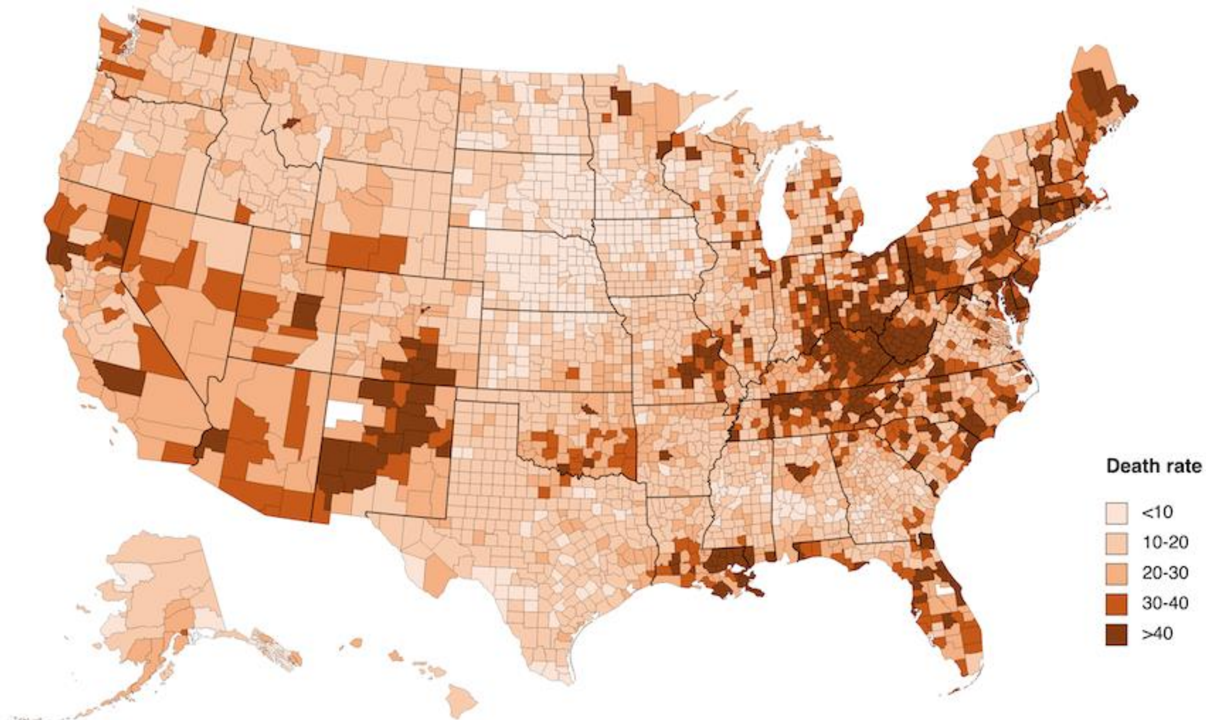


Figure 2. The implementation of PDMPs in different states

This figure shows the states that implemented the PDMPs in our sample period. States are color-coded based on the year of implementation of the programs. States without color either do not have PDMPs from 1999 to 2020 or implement PDMPs beyond our sample period.

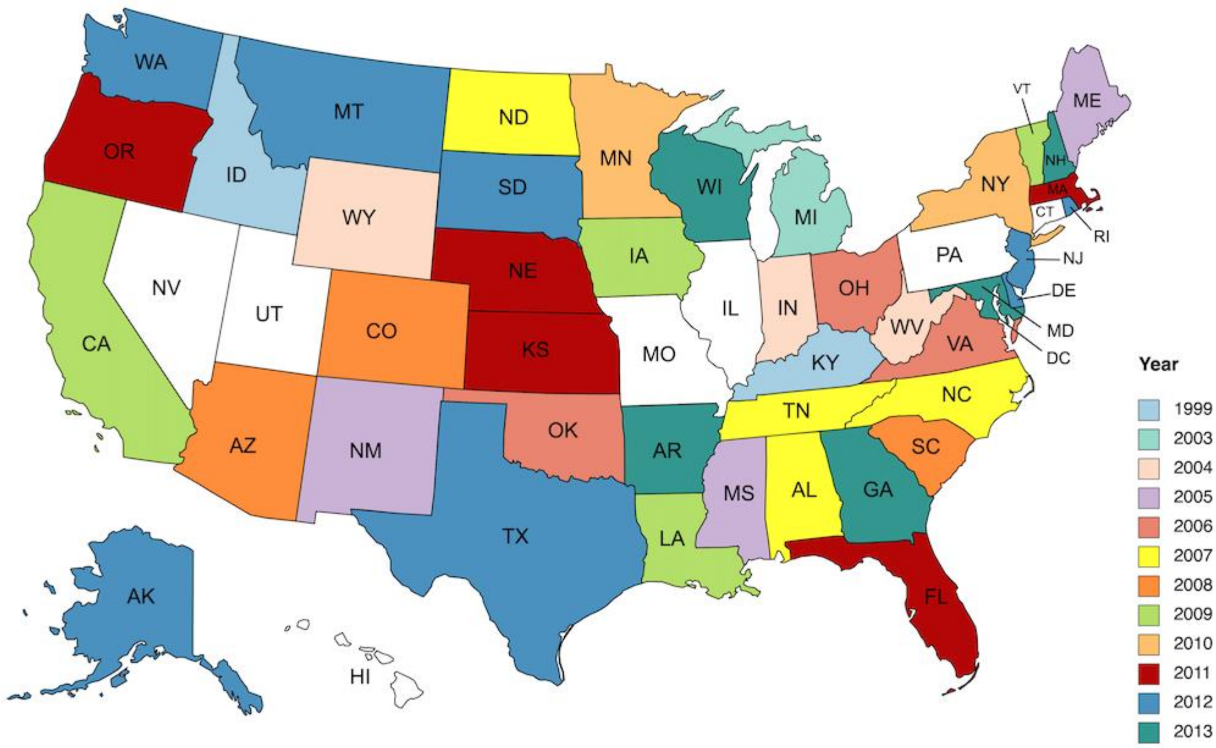
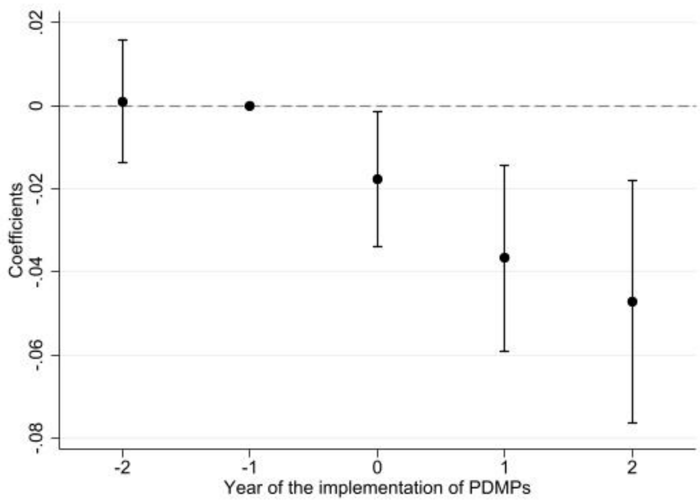
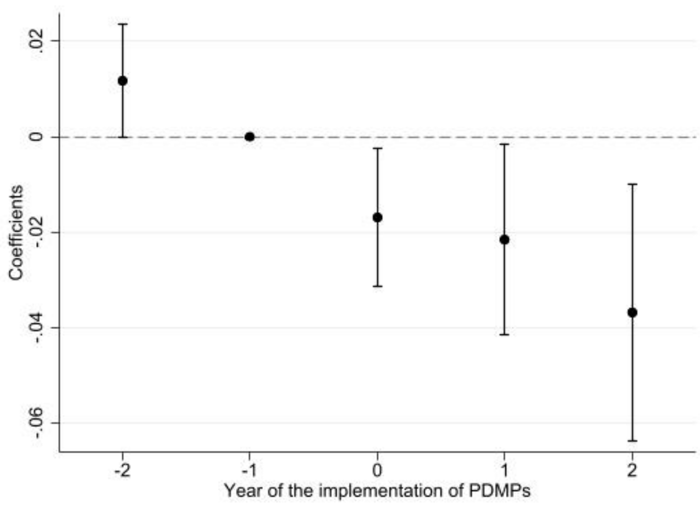


Figure 3. Dynamic effects

This figure shows the dynamic effects of PDMP implementation from Table 3. Year 0 is the implementation year of PDMPs. All control variables in Table 2 are included. Firm and year fixed effects are included, and standard errors are clustered at the county level. Financial and utility firms are excluded. We restrict the sample to a five-year window and remove firms that relocated their headquarters to other states from our sample. All continuous variables are winsorized at 1% and 99% levels. Capped spikes indicate statistical significance at the 10% level.



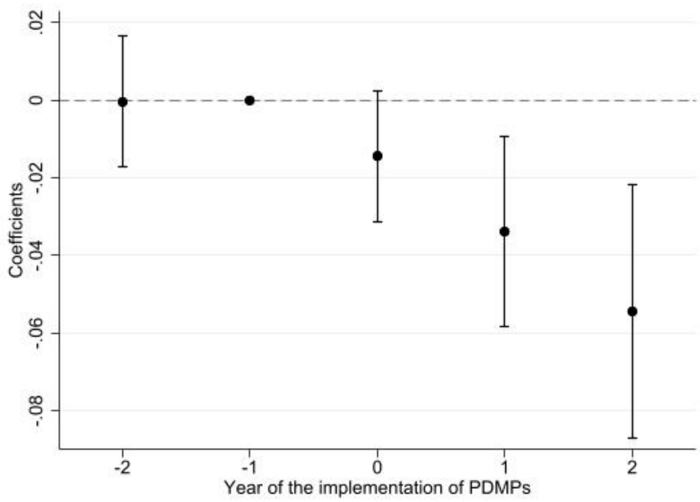
(a) Effect of PDMPs on NMFIS



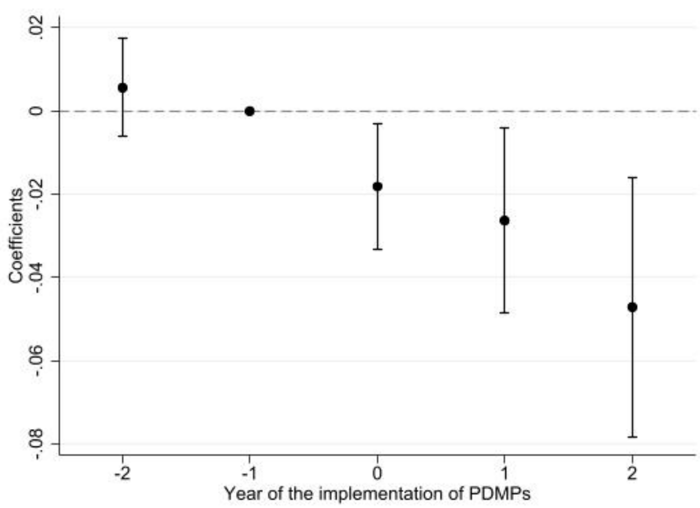
(b) Effect of PDMPs on SlopeD

Figure 4. PSM method: Dynamic effects

This figure shows the dynamic effects of PDMP implementation from Table 4 by using the PSM method. Year 0 is the implementation year of PDMPs. All control variables in Table 2 are included. Firm and year fixed effects are included, and standard errors are clustered at the county level. We restrict the sample to a five-year window and remove firms that relocated their headquarters to other states from our sample. We use the PSM method to match firm characteristics in the year prior to the implementation of PDMPs. All continuous variables are winsorized at 1% and 99% levels. Capped spikes indicate statistical significance at the 10% level.



(a) Effect of PDMPs on NMFIS



(b) Effect of PDMPs on SlopeD

Table 1. Summary statistics

This table presents pool summary statistics of firm-level, county-level characteristics, and firm-level correlation matrix. SlopeD measures the steepness of the function that relates implied volatility to moneyness. NMFIS is a measure of the negative model-free implied skewness. Death rate is the opioid-related death rate. The main sample period is from 1999 to 2020. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. Detailed variable definitions are provided in Appendix A.

Variables	Observation	Mean	STD	P25	P50	P75
Panel A: Firm-year level						
NMFIS	35,890	0.367	0.392	0.108	0.355	0.603
SlopeD	35,890	0.376	0.355	0.148	0.260	0.491
Death rate	35,890	13.324	8.188	7.959	11.058	16.316
Log(Assets)	35,890	6.897	1.742	5.675	6.842	8.036
Dividends/net income	35,890	0.140	0.455	0.000	0.000	0.180
Debt/assets	35,890	0.225	0.217	0.015	0.191	0.353
EBIT/assets	35,890	0.027	0.206	0.010	0.074	0.125
CapEx/assets	35,890	0.051	0.057	0.017	0.033	0.063
Book-to-market	35,890	0.457	0.395	0.206	0.372	0.617
Returns	35,890	0.168	0.734	-0.235	0.041	0.349
CAPM beta	35,890	1.378	0.853	0.819	1.238	1.774
Volatility	35,890	0.137	0.079	0.081	0.116	0.169
Institutional ownership	35,890	0.698	0.266	0.547	0.757	0.896
Panel B: County-year level						
Death rate	6,536	14.673	9.240	8.177	12.287	18.344
Population level	6,536	12.735	1.042	12.028	12.811	13.460
Per capita income	6,536	10.642	0.286	10.437	10.615	10.807
Population growth	6,536	0.009	0.011	0.002	0.007	0.014
Employment growth	6,536	0.008	0.022	-0.003	0.010	0.021

Panal C	Var1	Var2	Var3	Var4	Var5	Var6	Var7	Var8	Var9	Var10	Var11	Var12	Var13
NMFIS	1.000												
SlopeD	0.547	1.000											
Death rate	0.146	0.287	1.000										
Log(Assets)	0.404	0.051	0.095	1.000									
Dividends/net income	0.138	0.097	0.061	0.182	1.000								
Debt/assets	0.085	0.046	0.135	0.337	0.094	1.000							
EBIT/assets	0.308	0.133	-0.001	0.439	0.147	0.039	1.000						
CapEx/assets	-0.024	-0.074	-0.049	0.039	-0.007	0.076	0.080	1.000					
Book-to-market	-0.172	-0.033	-0.021	0.046	-0.052	-0.121	0.003	0.027	1.000				
Returns	0.033	0.014	-0.009	-0.113	-0.041	-0.039	-0.005	-0.066	-0.255	1.000			
CAPM beta	-0.177	-0.101	-0.053	-0.182	-0.141	-0.054	-0.207	-0.040	0.043	0.060	1.000		
Volatility	-0.355	-0.247	-0.172	-0.470	-0.210	-0.093	-0.422	-0.006	0.023	0.220	0.439	1.000	
Institutional ownership	0.336	0.244	0.129	0.369	-0.000	0.070	0.341	-0.034	-0.021	-0.047	-0.074	-0.349	1.000

Table 2. The effect of opioid crisis on firm downside tail risk implied from the option market

This table presents firm-level regressions of downside tail risk on opioid crisis risk. NMFIS is a measure of the negative model-free implied skewness. SlopeD measures the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate. Firm and year fixed effects are included, and standard errors are clustered at the county level in columns (1) and (2), and double clustered at the county and year levels in columns (3) and (4). The sample period is from 1999 to 2020. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

Dependent variable	NMFIS (1)	SlopeD (2)	NMFIS (3)	SlopeD (4)
Death rate	0.0025***	0.0020***	0.0025***	0.0020***
	(3.82)	(3.29)	(4.00)	(3.04)
Log(Assets)	0.0753***	0.0088	0.0753***	0.0088
	(13.19)	(1.61)	(7.64)	(1.19)
Dividends/net income	0.0008	0.0105**	0.0008	0.0105**
	(0.18)	(2.50)	(0.17)	(2.26)
Debt/assets	-0.1443***	-0.1109***	-0.1443***	-0.1109***
	(-7.43)	(-5.11)	(-6.15)	(-4.88)
EBIT/assets	0.0173	0.0304	0.0173	0.0304
	(0.92)	(1.32)	(0.91)	(1.33)
CapEx/assets	0.2096***	0.0767	0.2096**	0.0767
	(3.27)	(1.43)	(2.78)	(1.36)
Book-to-market	-0.1529***	-0.0589***	-0.1529***	-0.0589***
	(-16.27)	(-7.10)	(-6.72)	(-4.41)
Returns	0.0259***	0.0122***	0.0259***	0.0122**
	(7.60)	(4.07)	(4.54)	(2.76)
CAPM beta	0.0092*	0.0058	0.0092	0.0058
	(1.91)	(1.22)	(1.32)	(1.09)
Volatility	-0.2230***	-0.2866***	-0.2230***	-0.2866***
	(-4.63)	(-7.71)	(-3.40)	(-4.75)
Institutional ownership	0.1076***	0.1550***	0.1076***	0.1550***
	(5.53)	(9.08)	(4.56)	(5.80)
Population level	-0.0071	0.0032	-0.0071	0.0032
	(-1.02)	(0.48)	(-0.95)	(0.42)
Per capita income	-0.0123	0.0184	-0.0123	0.0184
	(-0.54)	(0.87)	(-0.49)	(1.05)
Population growth	0.1457	0.0005	0.1457	0.0005
	(0.33)	(0.00)	(0.34)	(0.00)
Employment growth	0.1554	-0.0504	0.1554	-0.0504
	(0.91)	(-0.32)	(0.93)	(-0.31)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	County	County	County, Year	County, Year
Observations	35,890	35,890	35,890	35,890
Adj. R^2	0.546	0.546	0.558	0.558

Table 3. The effect of PDMP implementation on opioid crisis and downside tail risk implied from the option market: DID analysis

This table presents the impact of PDMP implementation on opioid crisis risk and downside tail risk. NMFIS is a measure of the negative model-free implied skewness. SlopeD measures the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate. PDMP is a dummy variable that equals one after the year in which a firm's headquarter state adopts PDMPs. All county-level control variables are included in column (1), and all control variables in Table 2 are included in columns (2) and (3). County and year fixed effects are included in column (1), and firm and year fixed effects are included in columns (2) and (3). Standard errors are clustered at the county level. We restrict the sample to a five-year window and remove firms that relocated their headquarters to other states from our sample. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

Dependent variable	Death rate	NMFIS	SlopeD
	(1)	(2)	(3)
PDMP	-0.6992***	-0.0304**	-0.0275***
	(-2.78)	(-2.52)	(-2.64)
Controls	Yes	Yes	Yes
Firm FE	No	Yes	Yes
County FE	Yes	No	No
Year FE	Yes	Yes	Yes
Observations	1,982	9,845	9,845
Adj. R^2	0.776	0.592	0.571

Table 4. Alternative identification method: PSM method

This table presents the impact of PDMP implementation on opioid crisis risk and downside tail risk. NMFIS is a measure of the negative model-free implied skewness. SlopeD measures the steepness of the function relating implied volatility to moneyness. Death rate is the opioid-related death rate. PDMP is a dummy variable that equals one after the year in which a firm's headquarter state adopts PDMPs. Post is a dummy variable that equals one after the year adopts PDMPs for both treated firms and their control firms. Panel A shows the PSM-DID regression results for the opioid crisis and downside tail risks, while Panel B presents the PSM-DID regression results for the opioid crisis and matched variables. The sample is restricted to a five-year window and firms that relocated their headquarters to other states are removed. All county-level control variables are included in Panel A column (1), and all control variables in Table 2 are included in Panel A columns (2) and (3). County and year fixed effects are included in Panel A column (1), while firm and year fixed effects are included in both Panel A columns (2) and (3) and Panel B. Standard errors are clustered at the county level. Financial and utility firms are excluded. All continuous variables are winsorized at the 1% and 99% levels. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

Panel A: Regression for downside tail risks			
Dependent variable	Death rate	NMFIS	SlopeD
	(1)	(2)	(3)
PDMP	-0.9168**	-0.0307**	-0.0357***
	(-2.08)	(-1.99)	(-2.76)
Post	0.5065	0.0041	0.0096
	(1.42)	(0.47)	(1.17)
Controls	Yes	Yes	Yes
Firm FE	No	Yes	Yes
County FE	Yes	No	No
Year FE	Yes	Yes	Yes
Observations	1,632	8,470	8,470
Adj. R^2	0.803	0.620	0.579

Panel B: Regression for matched variables						
Dependent variable	Log(Assets)	Debt/asset s	EBIT/assets	CapEx/asset s	Book-to-market	Institutiona l ownership
	(1)	(2)	(3)	(4)	(5)	(6)
PDMP	-0.0153	-0.0040	-0.0068	0.0018	0.0147	0.0052
	(-0.70)	(-0.67)	(-1.37)	(0.84)	(0.89)	(0.43)
Post	0.0011	0.0013	0.0023	0.0006	-0.0139	-0.0031
	(0.11)	(0.39)	(1.21)	(0.49)	(-1.30)	(-0.39)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,470	8,470	8,470	8,470	8,470	8,470
Adj. R^2	0.978	0.852	0.769	0.761	0.629	0.746

Table 5. The effect of opioid crisis on firm labor productivity

This table presents firm-level regressions of firm labor productivity on opioid crisis risk. Labor productivity is the ratio of sales to the number of employees in year *t*. Death rate is the opioid-related death rate in year *t*. Job posting is the number of jobs posted by a firm within the year *t+1* divided by sales of year *t*. Computer job posting is the number of job postings related to computer occupations posted by a firm within the year *t+1* divided by sales of year *t*. Firm and year fixed effects are included, and standard errors are clustered at the county level. Financial and utility firms are excluded. The sample period is from 1999 to 2020 and all continuous variables are winsorized at 2.5% and 97.5% levels in column (1). The sample period is from 2007 to 2020 and all continuous variables are winsorized at 1% and 99% levels in columns (2) and (3). T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

Dependent variable	Labor productivity (1)	Job posting (2)	Computer job posting (3)
Death rate	-1.3154**	0.0059**	0.0006***
	(-2.37)	(2.30)	(2.70)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	35,890	15,589	15,589
Adj. R^2	0.868	0.567	0.634

Table 6. The effect of labor intensity

This table presents firm-level regressions of downside tail risk on opioid crisis risk through the labor intensity channel. NMFIS is a measure of the negative model-free implied skewness. SlopeD measures the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate. In columns (1) and (2) or columns (3) and (4), we classify firms into two subgroups based on the labor intensity at the industry level. Firms in manufacturing, construction, and mining industries are categorized as "High Labor Intensity", while firms in other industries are categorized as "Low Labor Intensity". Firm and year fixed effects are included, and standard errors are clustered at the county level. The sample period is from 1999 to 2020. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

Dependent variable	NMFIS		SlopeD	
	High Labor Intensity	Low Labor Intensity	High Labor Intensity	Low Labor Intensity
	(1)	(2)	(3)	(4)
Death rate	0.0031***	0.0015	0.0023***	0.0011
	(3.87)	(1.55)	(2.90)	(1.14)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	21,580	14,310	21,580	14,310
Adj. R^2	0.553	0.541	0.564	0.553
Difference (High-Low)	0.002***		0.001**	
p-value	(0.000)		(0.010)	

Table 7. The effect of labor supply

This table presents firm-level regressions of downside tail risk on opioid crisis risk through the labor supply channel. NMFIS is a measure of the negative model-free implied skewness. SlopeD measures the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate. In columns (1) and (2) or columns (3) and (4), we classify firms into two subgroups based on the labor supply at the county level. The labor supply is measured by the labor force rate of each county each year. Firms located in the county with labor supply below the median are categorized as "Low Labor Supply", while firms located in the county with labor supply above the median are categorized as "High Labor Supply". Firm and year fixed effects are included, and standard errors are clustered at the county level. The sample period is from 1999 to 2020. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

Dependent variable	NMFIS		SlopeD	
	Low Labor Supply	High Labor Supply	Low Labor Supply	High Labor Supply
	(1)	(2)	(3)	(4)
Death rate	0.0037***	0.0021***	0.0027***	0.0015*
	(3.33)	(2.58)	(3.01)	(1.76)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	15,902	19,982	15,902	19,982
Adj. R^2	0.540	0.564	0.565	0.568
Difference (Low-High)	0.002***		0.001***	
p-value	(0.000)		(0.000)	

Table 8. The effect of workplace safety

This table presents firm-level regressions of downside tail risk on opioid crisis risk through the workplace safety channel. NMFIS is a measure of the negative model-free implied skewness. SlopeD measures the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate. In columns (1) and (2) or columns (3) and (4), we classify firms into two subgroups based on firm employee health and safety incidents in the previous year, which can be obtained from the RepRisk database. Firms that experienced employee health and safety incidents are categorized as "Low Workplace Safety", while firms that did not have any such incidents are categorized as "High Workplace Safety". Firm and year fixed effects are included, and standard errors are clustered at the county level. The sample period is from 2008 to 2020. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

Dependent variable	NMFIS		SlopeD	
	Low Workplace Safety	High Workplace Safety	Low Workplace Safety	High Workplace Safety
	(1)	(2)	(3)	(4)
Death rate	0.0048***	-0.0001	0.0044***	-0.0002
	(2.84)	(-0.05)	(3.03)	(-0.24)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,513	4,183	1,513	4,183
Adj. R^2	0.528	0.568	0.652	0.649
Difference (Low-High)	0.005***		0.005***	
p-value	(0.000)		(0.000)	

Table 9. The effect of the local economy

This table presents firm-level regressions of downside tail risk on opioid crisis risk through the local economic channel. NMFIS is a measure of the negative model-free implied skewness. SlopeD measures the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate. In columns (1) and (2) or columns (3) and (4), we classify firms into two subgroups based on the growth rate of GDP per capita at the county level. GDP per capita is calculated by dividing the GDP of a county by its total population in a given year. Firms located in a county with the growth rate of GDP per capita below the median are categorized as "Low GDP Growth", while firms located in a county with the growth rate of GDP per capita above the median are categorized as "High GDP Growth". Firm and year fixed effects are included, and standard errors are clustered at the county level. The sample period is from 2002 to 2020. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

Dependent variable	NMFIS		SlopeD	
	Low GDP Growth	High GDP Growth	Low GDP Growth	High GDP Growth
	(1)	(2)	(3)	(4)
Death rate	0.0027***	0.0022***	0.0019**	0.0015**
	(2.66)	(2.58)	(2.08)	(2.16)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	13,872	18,052	13,872	18,052
Adj. R^2	0.536	0.567	0.561	0.564
Difference (Low-High)	0.001		0.000	
p-value	(0.200)		(0.240)	

Table 10. Alternative measures for the opioid crisis from firm establishments

This table presents alternative measures for opioid crisis risk on downside tail risk from the perspective of firm establishments. NMFIS is a measure of the negative model-free implied skewness. SlopeD measures the steepness of the function that relates implied volatility to moneyness. Death rate EW is calculated as the weighted average death rate for each firm based on the proportion of employees in each establishment. Death rate SW is computed as each firm's weighted average death rate based on its proportion of sales volume in each establishment. Firm and year fixed effects are included, and standard errors are clustered at the firm level. The sample period is from 1999 to 2020. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

Dependent variable	NMFIS	SlopeD	NMFIS	SlopeD
	(1)	(2)	(3)	(4)
Death rate EW	0.0031***	0.0022**		
	(2.83)	(2.04)		
Death rate SW			0.0034***	0.0025**
			(3.15)	(2.46)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	21,358	21,358	21,358	21,358
Adj. R^2	0.538	0.549	0.539	0.550

Table 11. Alternative measures for the opioid crisis

This table presents alternative measures for opioid crisis risk on downside tail risk. NMFIS is a measure of the negative model-free implied skewness. SlopeD measures the steepness of the function that relates implied volatility to moneyness. Death rate robust1 is the opioid-related death rate that restricts the sample to counties with more than 10 opioid-related deaths. Death rate robust2 is the opioid-related death rate that restricts multiple causes to natural and semi-synthetic opioids, other synthetic opioids, and heroin, and restricts deaths to more than 10 opioid-related deaths. Firm and year fixed effects are included, and standard errors are clustered at the county level. The sample period is from 1999 to 2020. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

Dependent variable	NMFIS	SlopeD	NMFIS	SlopeD
	(1)	(2)	(3)	(4)
Death rate robust1	0.0024***	0.0019***		
	(3.65)	(3.23)		
Death rate robust2			0.0044***	0.0029***
			(3.84)	(2.68)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	34,992	34,992	31,431	31,431
Adj. R^2	0.549	0.559	0.559	0.562

Table 12. Placebo test: Other death reasons

This table presents firm-level regressions of downside tail risk on other death reasons. NMFIS is a measure of the negative model-free implied skewness. SlopeD measures the steepness of the function that relates implied volatility to moneyness. All death rate is the all-cause death rate. TOP3 death rate is the top 3-cause death rate, including heart disease, cancer, and accidents. TOP1 death rate is the top 1-cause death rate, which is heart disease. Firm and year fixed effects are included, and standard errors are clustered at the county level. The sample period is from 1999 to 2020. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

Dependent variable	NMFIS	SlopeD	NMFIS	SlopeD	NMFIS	SlopeD
	(1)	(2)	(3)	(4)	(5)	(6)
All death rate	-0.0000	-0.0000				
	(-0.32)	(-0.00)				
TOP3 death rate			-0.0000	-0.0000		
			(-0.42)	(-0.17)		
TOP1 death rate					-0.0002	-0.0001
					(-0.95)	(-0.67)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35,890	35,890	35,890	35,890	35,888	35,888
Adj. R^2	0.545	0.557	0.545	0.557	0.545	0.557

Table 13. The effect of investor attention

This table presents firm-level regressions of downside tail risk on opioid crisis risk through the investor attention channel. NMFIS is a measure of the negative model-free implied skewness. SlopeD measures the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate. Investor attention is proxied by Google search volume growth rate at the state-year level. Each year, we divide all the states into two groups based on the growth rate of SVI. Firms headquartered in the states with investor attention above the median are categorized as "High Investor Attention", while other firms are categorized as "Low Investor Attention". Firm and year fixed effects are included, and standard errors are clustered at the county level. The sample period is from 2004 to 2020. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

Dependent variable	NMFIS		SlopeD	
	High Investor Attention	Low Investor Attention	High Investor Attention	Low Investor Attention
	(1)	(2)	(3)	(4)
Death rate	0.0027***	0.0016	0.0021***	0.0018**
	(3.01)	(1.62)	(2.77)	(2.03)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	13,826	12,116	13,826	12,116
Adj. R^2	0.565	0.552	0.565	0.544
Difference (High-Low)	0.001**		0.000	
p-value	(0.030)		(0.220)	

Appendix A. Definition of Variables

Variables	Definition	Source
Main variables		
NMFIS	NMFIS is computed using the standard formula for the skewness coefficient, as the third central moment of the risk-neutral distribution normalized by the risk-neutral variance (raised to the power of 3/2). In this paper, we use the negative model-free implied skewness constructed at yearly level (average of daily values), thus a higher value indicates a higher downside (left-) tail risk.	OptionMetrics
SlopeD	SlopeD is the slope coefficient by regressing the implied volatilities of out-of-the-money (OTM) puts with 30 days maturity and Black-Scholes delta ranging from -0.5 to -0.1 on their corresponding deltas and a constant term. The measure is constructed at yearly level (average of daily values). A higher value indicates a higher tail risk.	OptionMetrics
Death rate	The death rate is the number of opioid-related deaths, adjusted for county population (per 100,000).	CDC
Firm-level controls		
Log(Assets)	The logarithm of total assets (AT) at the end of the year.	Compustat
Dividends/net income	Dividends (DVT) at the end of the year divided by net income (NI) at the end of the year.	Compustat
Debt/assets	The sum of the book value of long-term debt (DLTT) and the book value of current liabilities (DLC) at the end of the year divided by total assets (AT) at the end of the year.	Compustat
EBIT/assets	Earnings before interest and taxes (EBIT) divided by total assets (AT) at the end of the year.	Compustat
CapEx/assets	Capital expenditures (CAPX) at the end of the year divided by total assets (AT) at the end of the year.	Compustat
Book-to-market	Difference between common equity (CEQ) and preferred stock capital (PSTK) at the end of the year divided by the equity market value (abs(PRCC_F)*CSHO) at the end of the year.	Compustat, CRSP

Returns	Stock price at the end of the year (PRCC_F) divided by the stock price at the end of the previous year, minus 1.	Compustat, CRSP
CAPM beta	Sensitivity of monthly stock returns to monthly market returns. The variable is computed for each month with a rolling window of 60 months. For each firm i, the variable corresponds to the β_i coefficient in the regression $Returns_{i,t} = constant + \beta_i Market\ Return_t$. We use averaged values over the year.	Kenneth French's Data Library, CRSP
Volatility	Standard deviation of monthly stock returns, computed for each month with a rolling window of the past 12 months. We use averaged values over the year.	CRSP
Institutional ownership	Fraction of outstanding shares owned by institutional investors at the end of the year.	Thomson-Reuters
Population level EW	Population level EW is computed as the weighted average population level for each firm based on the proportion of employees in each establishment.	Bureau of Economic Analysis (BEA), YTS
Per capita income EW	Per capita income EW is computed as the weighted average per capita income for each firm based on the proportion of employees in each establishment.	Bureau of Economic Analysis (BEA), YTS
Population growth EW	Population growth EW is computed as the weighted average population growth for each firm based on the proportion of employees in each establishment.	Bureau of Economic Analysis (BEA), YTS
Employment growth EW	Employment growth EW is computed as the weighted average employment growth for each firm based on the proportion of employees in each establishment.	Bureau of Labor Statistics (BLS), YTS
Population level SW	Population level SW is computed as the weighted average population level for each firm based on the proportion of sales in each establishment.	Bureau of Economic Analysis (BEA), YTS
Per capita income SW	Per capita income SW is computed as the weighted average per capita income for each firm based on the proportion of sales in each establishment.	Bureau of Economic Analysis (BEA), YTS
Population growth SW	Population growth SW is computed as the weighted average population growth for each firm based on the proportion of sales in each establishment.	Bureau of Economic Analysis (BEA), YTS

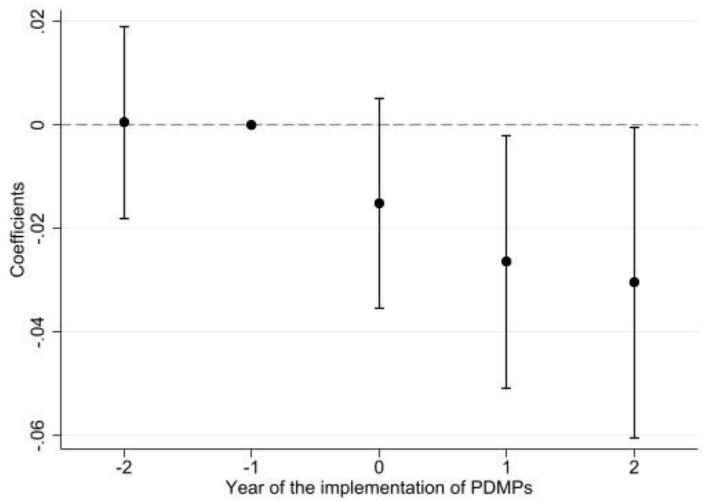
Employment growth SW	Employment growth SW is computed as the weighted average employment growth for each firm based on the proportion of sales in each establishment.	Bureau of Labor Statistics (BLS), YTS
County-level controls		
Population level	Population level is the logarithm of population number of each county for each year.	Bureau of Economic Analysis (BEA)
Per capita income	Per capita income is the logarithm of average income earned per person of each county for each year.	Bureau of Economic Analysis (BEA)
Population growth	Population growth is population growth rate of each county for each year.	Bureau of Economic Analysis (BEA)
Employment growth	Employment growth is employment growth rate of each county for each year.	Bureau of Labor Statistics (BLS)
Other variables		
Labor productivity	Labor productivity as the ratio of sales to the number of employees.	Compustat
Job posting	Job postings is defined as the number of jobs posted by a firm divided by sales each firm each year.	RavenPack Job Analytics
Computer job posting	Computer job posting is defined as the number of computer-related positions posted by a firm by sales each firm each year.	RavenPack Job Analytics
Death rate EW	Death rate EW is computed as the weighted average death rate for each firm based on the proportion of employees in each establishment.	CDC, YTS
Death rate SW	Death rate SW is computed as the weighted average death rate for each firm based on the proportion of sales volume in each establishment.	CDC, YTS
Death rate robust1	Death rate robust1 is the opioid-related death rate that restricts the sample to counties with more than 10 opioid-related deaths.	CDC
Death rate robust2	Death rate robust2 is the opioid-related death rate that restricts multiple causes to natural and semi-synthetic opioids, other synthetic opioids, and heroin. Besides, it restricts to more than 10 opioid-related deaths.	CDC
Death rate robust3	Death rate robust3 is the opioid-related death rate that restricts people to working-aged adults (aged 25–64 years) and restricts deaths to more than 10 opioid-related deaths.	CDC

Death rate robust4	Death rate robust4 is the opioid-related death rate that is proxied by dividing drug-related deaths by the county labor force (per 100,000).	Bureau of Labor Statistics (BLS), CDC
Death rate robust5	Death rate robust5 is the opioid-related death rate that excludes deaths related to intentional self-poisoning by drugs (ICD-10 codes: X60-X64).	CDC
All death rate	All death rate is the all-cause death rate, which is the number of all deaths, adjusted for county population (per 100,000).	CDC
TOP3 death rate	TOP3 death rate is the top 3-cause death rate, including heart disease, cancer, and accidents, which is the number of top 3 deaths, adjusted for county population (per 100,000).	CDC
TOP1 death rate	TOP1 death rate is the top 1-cause death rate, which is the number of heart disease deaths, adjusted for county population (per 100,000).	CDC

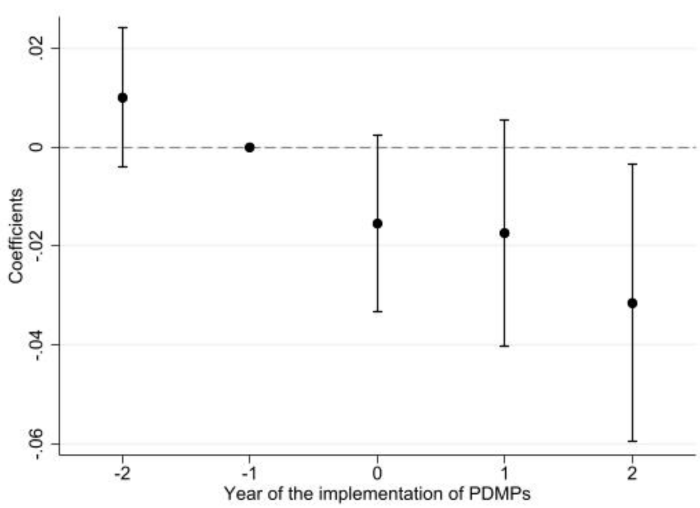
Appendix B

Figure B1. Stacked DID: Dynamic effects

This figure shows the dynamic effects of PDMP implementation from Table B3. Year 0 is the implementation year of PDMPs. All control variables in Table 2 are included. Firm-cohort and year-cohort fixed effects are included, and standard errors are clustered at the county-cohort level. We restrict the sample to a five-year window and remove firms that relocated their headquarters to other states from our sample. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. Capped spikes indicate statistical significance at the 10% level.



(a) Effect of PDMPs on NMFIS



(b) Effect of PDMPs on SlopeD

Table B1. Opioid crisis and downside tail risk implied from the option market: Exclude pharmaceutical and hospital industries

This table presents firm-level regressions of downside tail risk on opioid crisis risk. NMFIS is a measure of the negative model-free implied skewness. SlopeD measures the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate. Firm and year fixed effects are included, and standard errors are clustered at the county level in columns (1) and (2), and double clustered at the county and year levels in columns (3) and (4). We exclude firms in the pharmaceutical industry (SIC codes 2830-2839) and hospitals (SIC codes 8060-8069) from the main sample. The sample period is from 1999 to 2020. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

Dependent variable	NMFIS	SlopeD	NMFIS	SlopeD
	(1)	(2)	(3)	(4)
Death rate	0.0027***	0.0020***	0.0027***	0.0020***
	(4.05)	(3.18)	(4.19)	(2.84)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	County	County	County, Year	County, Year
Observations	32,047	32,047	32,047	32,047
Adj. R^2	0.540	0.540	0.554	0.554

Table B2. Summary statistics: DID analysis

This table presents pool summary statistics of firm-level and county-level characteristics in DID sample. SlopeD measures the steepness of the function that relates implied volatility to moneyness. NMFIS is a measure of the negative model-free implied skewness. Death rate is the opioid-related death rate. PDMP is a dummy variable that equals one after the year in which a firm's headquarter state adopts PDMPs. The sample period is from 1999 to 2020. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. Detailed variable definitions are provided in Appendix A.

Variables	Observation	Mean	STD	P25	P50	P75
Panel A: Firm-year level						
NMFIS	9,845	0.392	0.362	0.156	0.387	0.601
SlopeD	9,845	0.332	0.298	0.154	0.249	0.408
PDMP	9,845	0.380	0.485	0.000	0.000	1.000
Log(Assets)	9,845	6.967	1.686	5.804	6.934	8.091
Dividends/net income	9,845	0.150	0.468	0.000	0.000	0.207
Debt/assets	9,845	0.217	0.209	0.011	0.186	0.338
EBIT/assets	9,845	0.050	0.185	0.030	0.083	0.134
CapEx/assets	9,845	0.052	0.057	0.018	0.034	0.063
Book-to-market	9,845	0.477	0.382	0.234	0.397	0.637
Returns	9,845	0.173	0.691	-0.209	0.062	0.352
CAPM beta	9,845	1.368	0.820	0.825	1.239	1.757
Volatility	9,845	0.130	0.073	0.080	0.113	0.160
Institutional ownership	9,845	0.712	0.263	0.576	0.772	0.900
Panel B: County-year level						
Death rate	1,982	12.530	6.335	7.977	11.173	15.607
Population level	1,982	12.796	1.023	12.116	12.857	13.523
Per capita income	1,982	10.615	0.265	10.434	10.591	10.757
Population growth	1,982	0.009	0.011	0.002	0.008	0.014
Employment growth	1,982	0.004	0.024	-0.008	0.007	0.018

Table B3. Instrumental variable approach

This table presents the two-stage least squares (2SLS) regression results. NMFIS is a measure of the negative model-free implied skewness. SlopeD measures the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate. PDMP is the instrument for the death rate, which equals one after the year in which a firm's headquarter state adopts PDMPs. All control variables in Table 2 are included. Firm and year fixed effects are included, and standard errors are clustered at the county level. The sample period is from 1999 to 2020. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

Dependent variable	First stage	Second stage	
	Death rate	NMFIS	SlopeD
	(1)	(2)	(3)
PDMP	-1.9137***		
	(-3.33)		
$\widehat{Death\ rate}$		0.0201***	0.0162**
		(2.94)	(2.49)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	31,974	31,974	31,974
Adj. R^2	0.788	0.548	0.564

Table B4. Alternative identification method: Stacked DID analysis

This table presents the impact of PDMP implementation on opioid crisis risk and downside tail risk. NMFIS is a measure of the negative model-free implied skewness. SlopeD measures the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate. PDMP is a dummy variable that equals one after the year in which a firm's headquarter state adopts PDMPs. We restrict the sample to a five-year window and remove firms that relocated their headquarters to other states from our sample. All county-level control variables are included in column (1), and all control variables in Table 2 are included in columns (2) and (3). County-cohort and year-cohort fixed effects are included in column (1), and firm-cohort and year-cohort fixed effects are included in columns (2) and (3). Standard errors are clustered at the county-cohort level. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

Dependent variable	Death rate	NMFIS	SlopeD
	(1)	(2)	(3)
PDMP	-0.7638***	-0.0238*	-0.0257**
	(-2.90)	(-1.90)	(-2.21)
Controls	Yes	Yes	Yes
Firm-cohort FE	No	Yes	Yes
County-cohort FE	Yes	No	No
Year-cohort FE	Yes	Yes	Yes
Observations	4,055	19,414	19,414
Adj. R^2	0.827	0.613	0.615

Table B5. Summary statistics: Firm establishments

This table presents pool summary statistics of firm-level and county-level characteristics in firms' establishment sample. SlopeD measures the steepness of the function that relates implied volatility to moneyness. NMFIS is a measure of the negative model-free implied skewness. Death rate EW is calculated as the weighted average death rate for each firm based on the proportion of employees in each establishment. Death rate SW is computed as each firm's weighted average death rate based on its proportion of sales volume in each establishment. The sample period is from 1999 to 2020. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. Detailed variable definitions are provided in Appendix A.

Variables	Observation	Mean	STD	P25	P50	P75
NMFIS	21358	0.443	0.410	0.186	0.448	0.691
SlopeD	21358	0.431	0.380	0.176	0.294	0.588
Death rate EW	21358	14.924	6.914	10.010	13.153	18.517
Death rate SW	21358	14.882	6.895	9.995	13.143	18.442
Log(Assets)	21358	7.299	1.758	6.064	7.264	8.464
Dividends/net income	21358	0.179	0.495	0.000	0.000	0.272
Debt/assets	21358	0.236	0.209	0.048	0.210	0.357
EBIT/assets	21358	0.057	0.170	0.036	0.084	0.134
CapEx/assets	21358	0.048	0.049	0.017	0.033	0.061
Book-to-market	21358	0.438	0.366	0.206	0.365	0.595
Returns	21358	0.146	0.579	-0.186	0.064	0.332
CAPM beta	21358	1.290	0.739	0.793	1.178	1.653
Volatility	21358	0.118	0.066	0.073	0.101	0.144
Institutional ownership	21358	0.728	0.250	0.604	0.786	0.907
Population level EW	21358	13.212	1.106	12.613	13.356	13.936
Per capita income EW	21358	10.674	0.461	10.498	10.699	10.901
Population growth EW	21358	0.009	0.006	0.005	0.008	0.012
Employment growth EW	21358	0.010	0.017	0.004	0.013	0.019
Population level SW	21358	13.214	1.120	12.633	13.376	13.950
Per capita income SW	21358	10.675	0.471	10.498	10.698	10.903
Population growth SW	21358	0.009	0.007	0.005	0.008	0.012
Employment growth SW	21358	0.010	0.017	0.004	0.013	0.019

Table B6. The effect of employee gender

This table presents firm-level regressions of downside tail risk on opioid crisis risk through the employee gender channel. NMFIS is a measure of the negative model-free implied skewness. SlopeD measures the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate. We obtain the "Women Employees" measure from the Refinitiv database, constructed by dividing the number of women employees by the total number of company employees. The sample period for our analysis begins in 2002 due to the availability of data from the Refinitiv database. In columns (1) and (2) or columns (3) and (4), we classify firms into two subgroups based on the proportion of male employees in each firm obtained from the Refinitiv database. Firms with a proportion of male employees above the median proportion of male employees are categorized as "High Male Proportion", while firms with a proportion of male employees below the median are categorized as "Low Male Proportion". Firm and year fixed effects are included, and standard errors are clustered at the county level. The sample period is from 2002 to 2020. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

Dependent variable	NMFIS		SlopeD	
	High Male Proportion	Low Male Proportion	High Male Proportion	Low Male Proportion
	(1)	(2)	(3)	(4)
Death rate	0.0072***	-0.0017	0.0038***	0.0009
	(3.89)	(-0.96)	(2.71)	(0.53)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,478	1,446	1,478	1,446
Adj. R^2	0.653	0.567	0.753	0.754
Difference (High-Low)	0.009***		0.003**	
p-value	(0.000)		(0.020)	

Table B7. Alternative measures for the opioid crisis

This table presents alternative measures of opioid crisis risk on downside tail risk. NMFIS is a measure of the negative model-free implied skewness. SlopeD measures the steepness of the function that relates implied volatility to moneyness. Death rate robust3 is the opioid-related death rate that restricts people to working-aged adults (aged 25–64 years) and restricts deaths to more than 10 opioid-related deaths. Death rate robust4 is the opioid-related death rate that is proxied by dividing drug-related deaths by the county labor force (per 100,000). Death rate robust5 is the opioid-related death rate that excludes deaths related to intentional self-poisoning by drugs (ICD-10 codes: X60-X64). Firm and year fixed effects are included, and standard errors are clustered at the county level. The sample period is from 1999 to 2020. Financial and utility firms are excluded. All continuous variables are winsorized at 1% and 99% levels. T-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions are provided in Appendix A.

Dependent variable	NMFIS	SlopeD	NMFIS	SlopeD	NMFIS	SlopeD
	(1)	(2)	(3)	(4)	(5)	(6)
Death rate robust3	0.0014***	0.0012***				
	(3.70)	(3.29)				
Death rate robust4			0.0012***	0.0010***		
			(3.58)	(3.38)		
Death rate robust5						
					0.0024***	0.0018***
					(3.54)	(2.86)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,704	34,704	34,916	34,916	34,642	34,642
Adj. R^2	0.550	0.559	0.549	0.559	0.549	0.559