Opioid Crisis and Firm Downside Risks: Evidence from the Option Market*

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Abstract

We explore how the opioid crisis exposure affects firm downside risks implied from equity options. Using a large sample of public firms from 1999 to 2020, we find that firms headquartered in or having establishments in regions with higher opioid death rates have higher costs of protection against downside risks. Employing various robust difference-in-differences settings, we show that the effects are reversed following exogenous anti-opioid legislation, supporting a causal interpretation. Further analysis shows that the opioid crisis heightens firm risk by lowering labor productivity. We document greater impact among firms with higher reliance on labor and limited local labor supply.

Keywords: Opioid crisis, downside risk, option, labor productivity, labor supply

JEL classification: G32, E24, J24, I18

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1 Introduction

The opioid crisis refers to a widespread public health emergency characterized by the misuse, addiction, and overdose deaths associated with opioid drugs in the United States.[1] According to the National Institute on Drug Abuse (NIDA) and the Centers for Disease Control and Prevention (CDC), opioid drugs contribute to more than 75% of drug-involved overdose deaths in 2022.[2] Economic costs of the opioid crisis amounted to $1.5 trillion in 2020—37% more than that in 2017, based on the estimate of the U.S. Congress Joint Economic Committee (JEC). Recent finance and economics literature has started to explore the impact of the opioid crisis on public financing and corporate decisions.[3] However, little is known about the effect of the opioid crisis on firm risks, especially downside risks.

We construct firm-level downside risk measures from equity options and investigate the impact of the opioid crisis on firm downside risks by exploiting geographical variation of firm exposure to the opioid crisis and state-level staggered adoption of anti-opioid legislation. As snapshots of the opioid crisis across the U.S. in 2010 and 2020, Figures 1(a) and 1(b) show that, despite the wide impact of opioid drugs on the U.S., there is a lot of geographical heterogeneity in the death rates caused by drug use. The county-level death rates allow us to capture firms' exposure to the opioid crisis. Our panel regressions confirm that firms with high exposure to the opioid crisis have higher downside risks, as priced in the option market.[4] Using a staggered difference-in-differences (DiD) framework, we find that corporate downside risks drop after headquarters states implement Prescription Drug Monitoring Programs

[1] According to 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] See, for example, Cornaggia, Hund, Nguyen, and Ye (2022), Jansen (2023), and Ouimet, Simintzi, and Ye (2025).

[4] 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.

(PDMPs), which effectively reduce opioid death rates. We therefore establish causality that the opioid crisis elevates corporate downside risks.

Why would the opioid crisis increase corporate downside risks? Employees, as the most important and first stakeholders of a company, could be heavily influenced by the opioid crisis for several reasons. First, employees addicted to opioid drugs often exhibit higher rates of absenteeism (missing work) and presenteeism (being at work but not functioning effectively).[5] Second, even if employees are not directly affected by the side effects of opioid drugs, they might suffer from the negative consequences of opioid drug addiction in their social network. For example, an employee might be distracted from work when her family members or close friends are addicted to opioids. Last, the opioid crisis could increase labor market frictions, as it gets harder for firms to find employee replacements when there is a turnover.[6] All these reasons could adversely influence firms' workforce and productivity. In addition, employees with opioid use disorders impose higher costs on their employers, particularly through health insurance and workers' compensation. When firms fail to internalize labor costs associated with the opioid crisis, firms face higher downside risks as the probability of negative outcomes increases.[7]

Ouimet, Simintzi, and Ye (2025) show that firms respond to the labor shortages resulting from the opioid crisis by investing more in technology and replacing relatively scarcer labor with capital. If firms are able to adapt to the labor crisis caused by opioid abuse quickly, for example, by replacing less productive labor with IT technologies, then the opioid crisis is expected to have no or minimal effects on corporate downside risks. Thus, it is an empirical

[5] Workers with substance use disorders take nearly 50% more days of unscheduled leave than other workers, have an average turnover rate 44% higher than that for the workforce as a whole, and are more likely to experience occupational injuries that result in time away from work. See Goplerud, Hodge, and Benham (2017) for a more detailed analysis.

[6] According to Krueger (2017), the opioid epidemic accounts for 43% of the decline in men's labor force participation rate between 1999 and 2015, and 25% of the decline for women.

[7] According to a survey by National Safety Council (NSC), 75% of employers say their workplace is impacted by opioid abuse. Despite the widespread impact, only 17% of employers feel extremely well prepared to deal with the issue. See https://www.nsc.org/in-the-newsroom/poll-75-of-employers-say-their-workplace-impacted-by-opioid-use.

question whether or to what extent the opioid crisis affects corporate downside risks. We investigate it with comprehensive panel data and fill the gap.

Our measures of corporate downside risks come from equity options. Option market provides rich forward-looking information about perceived uncertainty and risk (Kelly, Pástor, and Veronesi (2016); Ilhan, Sautner, and Vilkov (2021); and 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) and An, Ang, Bali, and Cakici (2014)).[8] We construct two downside risk measures that are widely used in the literature.

Specifically, for each firm with equity options and on a daily basis, we select 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 sensitive to investor information flow and changes in perceived uncertainties and risks. If investors perceive a firm as riskier on the left tail, their demand and willingness to pay for protection against downside risk would be higher. The first measure that we extract from options is model-free implied skewness, NMFIS. NMFIS reflects the asymmetry of the risk-neutral distribution of underlying stock returns. Taking a negative sign, a more positive NMFIS value indicates a shift of the probability mass under the risk-neutral measure from the right to the left tail. The second measure is implied volatility slope, SlopeD, representing the relationship between left-tail implied volatility and moneyness for out-of-the-money (OTM) puts. A more positive value of SlopeD indicates that deeper OTM puts are relatively more expensive, suggesting a relatively higher cost of option protection against downside risk. For each firm-year, we take the average of daily NMFIS and SlopeD for our firm-year panel analysis.

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

Firm exposure to the opioid crisis is measured by the annual death rates from drug poisoning at the county level of the headquarters of the companies. Drug-poisoning death rates are a useful proxy for opioid abuse, as 75.79% of overdose deaths in the United States involve opioids in 2022 (CDC (2024)) and are commonly used in the literature (Jansen (2023) and Chen, Huang, Shi, and Yuan (2024)). After removing financial and utility firms and requiring non-missing variables, we assemble a sample of 35,847 firm-year observations from 4,496 unique public firms from 1999 to 2020.

We first run panel regressions of corporate downside risks on the opioid crisis exposure and document a positive association. A one standard deviation increase in opioid-related death rate is associated with an increase of 0.020 (0.016) in NMFIS (SlopeD), which is approximately 5% of the standard deviation of NMFIS (SlopeD). The findings validate our initial hypothesis that firms headquartered in regions with high degrees of opioid crisis are perceived as riskier on the left tail. The results hold when we use alternative measures of corporate exposure to the opioid crisis and include additional control variables.

An issue with our results might be that the firm's operations may not be centralized at its headquarters, leading to varying degrees of exposure to the opioid crisis in different locations. Therefore, we use the firm's data at the establishment level and construct firm-level opioid crisis measures using the average opioid death rates and employee-weighted opioid death rates from its various establishments. The results from the establishment-level data are consistent with our baseline results: higher exposure to the opioid crisis leads to an increase in downside risks.

Endogeneity concerns are non-negligible in our panel regressions. Alpert, Evans, Lieber, and Powell (2022) exploit the state-level policy variations of limiting the early entry and marketing of OxyContin and point out that the policy differences in 1996 explain variations in overdose deaths 20 years later. Although a non-pharmaceutical firm has little impact on regional-level policies of introducing opioid drugs, it is still possible that economic factors could affect both the downside risks of local firms and the drug use of residents. To mitigate omitted variable concerns, we use the staggered implementation of state-level Prescription Drug Monitoring Programs (PDMPs) as exogenous shocks, which has been documented to effectively reduce local misuse of opioids and opioid-related death rates (Cornaggia, Hund, Nguyen, and Ye (2022)).

Our staggered DiD analysis reveals a decrease in downside risk for firms located in states that have implemented PDMPs. After the adoption of PDMPs, the NMFIS (SlopeD) of treated firms decreases by 0.039 (0.030), which is about 10% (8%) of the standard deviation, respectively. This result supports a causal effect of the opioid crisis on corporate downside risks. Moreover, we use propensity score matching (PSM) and stacked DiD methods to address the potential bias from the staggered DiD approach. The significant reductions in corporate downside risks after headquarters states adopt PDMPs are robust to these alternative methods. In addition to using the shock at the headquarters level, we also construct a firm-level shock by aggregating the shocks experienced by each of the firm's establishments and find similar results.

Next, we identify the underlying mechanisms for the opioid crisis to increase corporate downside risks. The opioid crisis may lead to lower labor productivity and the shortage of qualified employees, thus contributing to higher corporate downside risks. Measured as sales per employee, labor productivity is significantly lower for firms headquartered in counties with high opioid-related death rates. Then, we examine how firms respond to the heightened downside risks posed by the opioid crisis. As a consequence of lower productivity, a firm more exposed to the opioid crisis posts more job opportunities. We find that both IT and non-IT job postings significantly increase with county-level opioid-related death rates. On the one hand, firms strive to replace labor with IT technologies by recruiting more IT jobs. On the other hand, not all vacancies could be replaced by technology, leading to more recruitment for non-IT jobs. Consistent with a local labor shortage conjecture, we find that firms exposed to the opioid crisis face greater recruitment difficulties.

After showing that the opioid crisis negatively affects labor productivity, we conduct a set of cross-sectional tests for more corroborating evidence. If lower labor productivity and labor replacement shortage are indeed the underlying mechanisms, our results should be more pronounced among firms heavily dependent on labor and in regions with low labor supply. First, we measure corporate reliance on labor by identifying labor-intensive industries. The operation outcomes of these labor-intensive industries are largely dependent on labor productivity. For example, the mining, construction, and manufacturing industries are labor-intensive. Automation is less technologically feasible as a large portion of the work relates to unpredictable physical work.[9] We find that the opioid crisis significantly increases local firms' downside risks only if the firms belong to labor-intensive industries. Though the effect of the opioid crisis on non-labor-intensive industries is also positive (but statistically insignificant), the magnitude is at most half of that on labor-intensive industries.

Second, local labor market frictions could also play an important role in the relationship between the opioid crisis and corporate downside risks. If firms can easily find replacement employees, the adverse impact of the opioid crisis should be mitigated. To measure labor supply, we consider the labor force participation rate, which is defined as the number of labor force over the total population. Consistent with our conjecture, we find that firms in counties with low labor supply suffer more from the opioid crisis.

Our analysis shows that the opioid crisis increases firm downside risks by lowering labor productivity and heightening labor market frictions. One alternative explanation is that local economic conditions weaken with the opioid crisis, and corporate downside risks rise at the same time.[10] This concern is more severe if the major customers of a firm are in the same county and the demand for the firm's output reduces. To address these concerns, we conduct two tests. First, we split the counties into two groups with high and low GDP growth rates. We do not find that our results differ across these two groups. Second, we identify firms

[9]See the report by McKinsey (2016) at https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/where-machines-could-replace-humans-and-where-they-cant-yet.

[10]Note that we include county-level macroeconomic variables in our regressions and the DiD analysis to control for the possible effect of local economic changes.

with local customers. When we exclude these firms from our analysis, we find quantitatively unchanged effects of the opioid crisis on downside risks. The results from these analyses are also consistent with our baseline results.

Our paper is related to recent economics and finance literature on 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, Hund, Nguyen, and Ye (2022)), reduced deposit growth and mortgage lending (Li and Ye (2024)), spillover effects on consumer finance (Jansen (2023)), lower labor participation rates (Krueger (2017); Park and Powell (2021); and Aliprantis, Fee, and Schweitzer (2023)), and lower real estate prices (D'Lima and Thibodeau (2023)). In addition, studies have shown that the opioid crisis negatively affects firm outcomes, including reduced innovation (Cornaggia, Hund, Pisciotta, and Ye (2023) and Chen, Huang, Shi, and Yuan (2024)) and decreased growth and investment (Ouimet, Simintzi, and Ye (2025)). Our paper complements these studies by presenting the first evidence that the opioid crisis increases firms' downside risks. The results of our study shed light on the possible distribution of firm outcomes in the opioid crisis.

Our paper also contributes to the literature on how firm risks are 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 option market. At the firm level, Dubinsky, Johannes, Kaeck, and Seeger (2019) extracts option-implied ex-ante earnings risks. Ilhan, Sautner, and Vilkov (2021) document that carbon-intense firms with higher climate policy uncertainty have higher downside risks implied from options. Cao, Goyal, Zhan, and Zhang (2024) find that ESG-related uncertainty is priced in the options market. Our study is the first to explore the impacts of a firm's labor conditions on the pricing of its options. Our paper also highlights the importance of taking the corporate external environment into account in option pricing studies.

Our paper is also related to the literature on human capital and corporate outcomes. This literature largely treats employees as intangible assets and documents that the market fails to recognize the value of employee satisfaction and ratings (Edmans (2011) and Green, Huang, Wen, and Zhou (2019)), and employee flexibility (Au, Dong, and Tremblay (2021)). Some recent studies attempt to understand the role of human capital on firm outcomes using more detailed data, such as employees' online profiles (Li, Lourie, Nekrasov, and Shevlin (2022)). Our paper complements this literature by studying the downside risks associated with employee health and productivity with clear identification strategies.

The remainder of the paper is organized as follows. We describe the data and the construction of the variables in Section 2. Section 3 presents our baseline results and robustness tests. Section 4 analyzes identification results. Section 5 provides the underlying channels of our results and further discussion. We conclude in Section 6.

2 Data and Measures

We collect data on drug and opioid poisoning death rates from the CDC WONDER Online Database from 1999 to 2020. Our sample contains public firms in the U.S., excluding those in the utility (SIC codes 4900-4949) and financial (SIC codes 6000-6999) industries. The stock price and return data for our sample firms are obtained from the Center for Research in Security Prices (CRSP). Individual equity options data is from OptionMetrics. Accounting information and institutional ownership data are collected from Compustat and Thomson Reuters (13F), respectively. 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 Exposure to the opioid crisis

To estimate a firm's exposure to the opioid crisis, we use the drug poisoning death rates in its headquarters county as a proxy. The death rate is defined as the number of drug-poisoning deaths adjusted for the county population (per 100,000), reflecting the severity level of the opioid crisis in a county. Following Jansen (2023) and according to the 10th Revision (ICD-10) codes of International Classification of Diseases, we attribute deaths with underlying causes 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 opioid-related deaths.[11] Note that the CDC suppresses death counts if a county has fewer than ten deaths of an underlying cause in a given year to protect the privacy of individuals. Therefore, for some county-year observations, we are not able to calculate opioid-related death rates. To address this data truncation issue, we supplement the suppressed data with the county-level drug poisoning mortality rates estimated using hierarchical Bayesian models provided by the CDC's National Center for Health Statistics (NCHS).[12]

One limitation of our proxy is that it is not a direct measure of the opioid-related death rates because drug-related deaths also include deaths resulting from other forms of substance abuse, such as cocaine, methamphetamine, and amphetamine. However, as shown by the CDC recently, more than 75.79% of drug-related deaths involve the use of prescription or nonprescription opioids. Our identification strategy, which exploits shocks that limit the prescription of opioids, also confirms that drug-related death rates, dominated by opioid-related death rates, significantly reduce after the policy shocks. Alternatively, we could restrict the death causes to specific opioid abuse. However, the truncation issue of this sample would become more severe, given that the number of deaths is more likely to be fewer than ten, and there are no estimated data. As a trade-off, we rely on the drug-related

[11] https://wonder.cdc.gov/mcd-icd10.html

[12] Our original sample consists of 36,329 firm-year observations with available firm option data and control variables. In this sample, there are 1,450 observations (3.99%) with missing opioid-related death rates due to suppression of data by the CDC. When we supplement the publicly reported CDC death rates with estimated death rates, our sample size is 35,847 firm-year observations, implying only 1.33% observations do not have the opioid-related death rates. The details of the estimation procedure can be found at https://www.cdc.gov/nchs/data-visualization/drug-poisoning-mortality/#techNotes. To further address potential concerns related to data suppression, we restrict our sample to counties with more than 10 overdose deaths and perform various robustness checks in Section 3.1.

death rates as a proxy of opioid-related death rates and acknowledge the limitation of this measure.

2.2 Downside risk measures

The option market contains forward-looking information about various uncertainties, such as political uncertainty (Kelly, Pástor, and Veronesi (2016)) and climate policy uncertainty (Ilhan, Sautner, and Vilkov (2021)). In addition, option traders are documented to have superior information to traders in other markets, and their information can predict future asset prices (Easley, O'Hara, and Srinivas (1998) and An, Ang, Bali, and Cakici (2014)). In this study, we use information from the option market to measure firm downside risks. Following Ilhan, Sautner, and Vilkov (2021), we use OTM call and put options with absolute values of 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, i.e., short-term options. 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 risks, NMFIS and SlopeD. The first measure, NMFIS, reflects the relative expensiveness of protection against left-tail events compared to right-tail events. Following Bakshi, Kapadia, and Madan (2003), 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. Specifically, NMFIS at time t for the period τ is constructed as:

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

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 (see Bakshi, Kapadia, and Madan (2003) and Ilhan, Sautner, and Vilkov (2021) for details). As NMFIS is influenced by both the left and right tails, a more positive value of the NMFIS 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 risk.

The second measure, SlopeD, is constructed by following Kelly, Pástor, and Veronesi (2016) and quantifies the relationship between left-tail implied volatility and moneyness. Specifically, we regress 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. 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 risk.

2.3 Summary statistics

As the CDC starts to report drug-poisoning death rates at the county level in 1999, we start our sample in 1999 and construct the two firm downside risk measures for all U.S. public firms in the OptionMetrics. We use augmented 10-X header data to link county-level opioid death rates according to the location of the firm's headquarters.[13] 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 include county-level variables as controls, including Log(Population), Log(Per capita income), Population growth, and Employment growth, following Gao, Lee, and Murphy (2020) and Cornaggia, Hund, Nguyen, and Ye (2022). After excluding utility firms (SIC codes 4900-4949) and financial firms (SIC codes 6000-6999), we

[13] https://sraf.nd.edu/sec-edgar-data/10-x-header-data/. County-years with missing death rates are supplemented with mortality rates estimated using hierarchical Bayesian models provided by the CDC's National Center for Health Statistics (NCHS). In robustness checks in Section 3.2, we also use the weighted average opioid death rate in the counties where the firm's establishments are located as a proxy for a firm's exposure to the opioid crisis.

obtain a sample of 35,847 firm-year observations from 4,496 unique public firms from 1999 to 2020.

Summary statistics of our sample are presented in Table 1. We report firm-year variables in Panel A, including headquarters' Death rate, NMFIS, SlopeD, and firm-level control variables. The mean of the Death rate is 13.326, showing that on average, 13 people out of 100,000 die due to drug overuse. The average NMFIS (SlopeD) for the sample is 0.367 (0.376), with a standard deviation of 0.392 (0.355). Our sample covers firms with significant cross-sectional variations in firm characteristics. For instance, the debt ratio at the 25th percentile is 0.015, while at the 75th percentile, it rises to 0.353. In Panel B, we report summary statistics for county-year observations. The average death rate at 14.673 is close to that of firm-year observations, indicating the firms are not concentrated in counties with extremely high or low death rates, allowing us to better estimate the overall impact of the opioid crisis on firm downside risks.

We report the correlation matrix in Panel C. The correlation between NMFIS and SlopeD is 0.547, which is reasonable because both variables capture downside risks, yet the information contained in the two variables is not exactly the same. NMFIS has relatively high correlations with firm assets (0.404) and institutional ownership (0.339), which we control for in the regression analysis.

One concern is that the level of the opioid crisis may not change much over time for different counties. Therefore, we might only capture cross-county variations. To see whether the opioid crisis differs from county to county and also evolves over time, we present the county-level heatmaps of opioid-related death rates in 2010 in Figure 1(a) and 2020 in Figure 1(b). We observe that almost every county in the U.S. suffers from the opioid crisis, showing its widespread impact across geographic regions, yet the severity of the crisis exhibits significant variations. Comparing the two heatmaps in 2010 and 2020 also leads to observable differences over time. These large time-series and cross-sectional variations of the opioid crisis allow us to comprehensively explore the relationship between firm exposure to the opioid crisis and the downside risks implied by the option market.

3 Baseline Results

3.1 Panel regression: Headquarters exposure to the opioid crisis

To formally examine the impact of exposure to the opioid crisis on firm downside risks, we begin our analysis with the following panel regression:

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

where $Downside\ risk_{i,t}$ for firm i in year t is proxied by NMFIS or SlopeD. $Death\ rate_{i,t}$ is the opioid-related death rate for firm i in its headquarters county 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, Institutional ownership, Log(Population), Log(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 exposure to the opioid crisis leads to a higher firm downside risk, we expect β to be significantly positive.

Panel A of Table 2 presents the baseline results. Consistent with our hypothesis, β is significantly positive across different specifications, suggesting a positive association between exposure to the opioid crisis and firm downside risk. Specifically, in columns (1) and (2), a one-standard-deviation increase in Death rate (8.192) is associated with an increase of 0.020 in NMFIS and an increase of 0.016 in SlopeD, which is approximately 5% of the standard deviation for both NMFIS and SlopeD. The economic magnitude is about half of the impact of industry-level carbon intensity on firm downside risks documented by Ilhan, Sautner, and

Vilkov (2021), indicating a significant and noteworthy effect.[14] These findings are consistent with our conjecture and suggest that the opioid crisis may exacerbate the firm downside risks.

To ensure the robustness and validity of our main results, we consider two alternative measures of the opioid death rate. First, we only use the drug-poisoning death rate from the CDC WONDER database as a proxy for the opioid death rate (Death rate_{Raw}). As noted earlier, the CDC suppresses county-years with fewer than ten deaths. Therefore, our sample size shrinks. However, the death rates should more accurately capture the regional opioid crisis. Second, we narrow the death rate to causes more related to opioids according to the multiple cause codes of the CDC ICD-10. Specifically, only deaths caused by natural and semi-synthetic opioids (T40.2), methadone (T40.3), other synthetic opioids (other than methadone) (T40.4), and heroin (T40.1) are included and defined as Death $\text{rate}_{\text{Narrow}}$. We report the results in Panel B of Table 2. The coefficients remain significant for both alternative measures.[15]

As mentioned in Section 2.1, the CDC suppresses death counts in cases where a county records fewer than ten deaths in a given year to protect individual privacy, and then we use NCHS estimated data to supplement our measure. One natural concern is that our regression results might be biased by these estimated death rates. To mitigate this possible bias, we restrict our analysis to larger counties, which are unlikely to have suppressed observations. First, we limit the sample to counties with populations exceeding 500,000, resulting in 29,024 firm-year observations, with only 0.17% of observations (50 firm-year observations) missing due to suppression of data. Next, we further restrict the sample to counties with popula-

[14] Ilhan, Sautner, and Vilkov (2021) show that a one-standard-deviation increase in a firm's log industry carbon intensity increases SlopeD by approximately 10% of the variable's standard deviation. Note that they use a sample of only S&P 500 firms, while we use all firms.

[15] We also construct other alternative measures of opioid death rates. First, we restrict the death rate to that of working-aged adults (aged 25–64 years), as it better reflects the local workforce quality and labor market frictions. Second, we calculate the opioid-related death rate by dividing the number of drug-related deaths by the size of a county's labor force (per 100,000). Third, we exclude deaths related to intentional self-poisoning by drugs (ICD-10 codes: X60-X64) to better capture drug addiction. These results, presented in Appendix Table B1 Panel A, are similar to the baseline results.

tions exceeding 1,000,000, yielding 18,281 firm-year observations with no missing data. The results of these robustness tests, presented in Panel C of Table 2, show magnitudes similar to the baseline regression, demonstrating that the NCHS estimated death rate does not systematically bias our findings.

Furthermore, we include additional local health indicators as control variables to rule out potential confounding effects. Specifically, we control for death rates from other causes, including the leading cause of death (heart disease), and the top three causes of death (heart disease, cancer, and accidents).[16] In addition, we control the percentage of individuals identified as heavy drinkers within a state (Alcohol), as excessive alcohol consumption is another significant public health issue that might influence firm-level risks.[17] The results, presented in Panel D of Table 2, reveal that the coefficient for the opioid death rate remains statistically significant after adding these control variables, whereas most of these control variables are statistically insignificant. This indicates that other causes of mortality and heavy alcohol consumption do not have a meaningful impact on firm downside risks. These results highlight the distinct and non-negligible influence of the opioid crisis on firm downside risks as well as reinforce the robustness of our conclusions.

An alternative approach to examine the uniqueness of the opioid crisis is placebo tests. In Panel B of Appendix Table B1, we replace the opioid-related death rates with heart disease deaths or deaths from the top three causes. These results allow us to see whether firm downside risk responds to general health conditions in the firm's headquarters county. Consistent with our observations in Panel D of Table 2, all the other health factors fail to yield a significant impact on firm downside risks.

As the opioid crisis becomes a national health emergency, some healthcare and pharmaceutical companies have been sued for producing and disseminating opioid-related drugs

[16] See the detailed information at https://www.cdc.gov/nchs/fastats/leading-causes-of-death.htm. According to ICD-10 death codes, heart disease deaths include deaths coded as I00–I09, I11, I13, and I20–I51. Cancer deaths are coded as C00–C97. Accidents (unintentional injuries) deaths are coded as V01-X59 and Y85-Y86.

[17] Alcohol data is sourced from the annual alcohol consumption survey conducted by the CDC, covering the period from 2001 to 2020. https://www.cdc.gov/brfss/annual_data/annual_2023.html

while downplaying side effects. Including these firms in our sample may lead to a downward bias in our results, as downside risk increases with (potential) litigation risks. We then exclude firms in the healthcare (SIC codes 8011-8099) and pharmaceutical (SIC codes 2830-2839) industries and then repeat the baseline analysis. The results shown in Appendix Table B2 remain similar to the baseline results.[18]

3.2 Alternative measures of exposure to the opioid crisis: Establishment data

In our baseline results, we measure firm-level exposure to the opioid crisis using the opioid death rate of the firm's headquarters county. Since firm operations may not be concentrated at its headquarters and are likely spread across different establishments, using the opioid-related death rate at its headquarters could not capture the local challenges faced by the establishments. Therefore, in this subsection, we use the establishment-level data and construct alternative firm-level opioid crisis measures by averaging the opioid-related death rate across the establishment counties of each firm.

Establishment-level data are obtained from the Your-Economy Time-Series (YTS) database, including establishment location, number of employees, and sales volume.[19] We only include economically important establishments, i.e., those with more than 10 employees.[20] Using the drug-poisoning deaths of counties where the establishments are located, we construct two alternative firm-level measures of the opioid-related death rates. First, we take the average of establishment-county death rates as Death $\text{rate}_{\text{Mean}}$. Second, we take the employee-number-weighted average of establishment-county death rates for a firm and label it as Death rate_{EW}.

[18]In unreported tests, we examine how exposure to the opioid crisis influences healthcare and pharmaceutical firms. We find no significant results. It is possible that the benefits, for example, from providing treatments and services to people with opioid-related issues, offset with the litigation risks or weakened employee productivity.

[19]YTS is owned by the Business Dynamics Research Consortium (BDRC) at the University of Wisconsin, and is commonly used in the literature (see, for example, Campello, Gustavo, d'Almeida, and Kankanhalli (2022) and Ghent (2021)).

[20]Yet, removing this restriction has no material impact on our results.

Panel A of Table 3 reports the summary statistics of this sample, which has 21,998 firm-year observations. [21]

Then we rerun our baseline regressions using the opioid exposure aggregated from establishments. As shown in Panel B of Table 3, the results are largely consistent with the baseline results.[22] A one-standard-deviation increase in Death $\text{rate}_{\text{Mean}}$ (6.606) is associated with a 0.023 (0.017) increase in NMFIS (SlopeD), corresponding to approximately 6% (4%) of the standard deviation. The measures constructed using establishment-level data more comprehensively capture the overall exposure of firms to the opioid crisis, further demonstrating the robustness of our results.

4 Identification Strategy

4.1 Staggered Implementation of Prescription Drug Monitoring Programs (PDMPs)

Our baseline results may be subject to possible endogeneity issues, such as omitted variables. For example, even though we include county-level macroeconomic variables in our regressions, it is still plausible that local economic factors could affect both the downside risks of local firms and the drug use distortions of residents. To mitigate these concerns, we utilize the staggered implementation of state-level Prescription Drug Monitoring Programs (PDMPs) as exogenous shocks, which aims to reduce opioid abuse and death. We then conduct a staggered difference-in-differences (DID) test to identify the causal impact of the opioid crisis on the downside risks.

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 use of prescription drugs, to prevent

[21] The reduction in sample size is because not all of our sample firms have a valid establishment record in the YTS database.

[22] The results also hold if we construct the death rate using establishment sales as weights.

the abuse of prescription medications, and to improve patient safety. By providing physicians with access to comprehensive and up-to-date information on the patient's prescription history, physicians can refuse 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 Prescription Drug Abuse Policy System provides the implementation time of PDMPs in different states up to 2017.[23] Figure 2 presents the implementation time of PDMPs across states in the U.S.

Previous evidence indicates that PDMPs lead to fewer opioid pills prescribed (Surratt et al. (2014) and Winstanley et al. (2018)), and could reduce opioid-related death rates (Cornaggia, Hund, Nguyen, and Ye (2022)). To confirm that the adoption of PDMPs effectively reduces the opioid-related death rate in our sample, we run the following county-year level regression:

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

where $PDMP_{s,t}$ is a dummy variable that equals one for years after the adoption of PDMP for a state s. $Controls_{c,t-1}$ are county-level control variables, including Log(Population), Log(Per capita income), Population growth, and Employment growth. We include county and year fixed effects and cluster the standard errors at the state level. As shown in column (1) of Table 4, the coefficient on $PDMP_{s,t}$ is negative and significant. The effect is substantial, with a decrease in the Death rate of approximately 1.966 per 100,000 people, corresponding to a nearly 21% reduction of the county-level standard deviation (1.966/9.304), indicating that the adoption of PDMPs effectively reduces opioid-related death rates.

Next, we investigate the impacts of PDMPs implementation on firm downside risks by running the following regression:

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

[23] Detailed information can be found at https://pdaps.org/datasets/pdmp-implementation-dates. For the states with missing information, we manually search for the time of PDMPs implementation for our sample period.

where $Downside\ risk_{i,t}$ is the downside risk, proxied by NMFIS or SlopeD, for firm i in year t. $PDMP_{s,t}$ is a dummy variable that equals one after the year of adoption of the PDMP for the firm i located in the state s. We include all control variables from Table 2, and remove firms that relocated their headquarters to other states during our sample period.[24] We include year and firm fixed effects and cluster standard errors at the state level. If the adoption of PDMPs lowers firm downside risks by mitigating the local opioid crisis, β should be significantly negative.

The results are reported in Table 4. Columns (2) and (3) show that when the headquarters states implement PDMPs, firms have lower downside risks. Specifically, after PDMP adoption, the firms' NMFIS decreases by 0.039, and SlopeD drops by 0.030, equivalent to 10% and 8% of the variables' standard deviations for NMFIS (0.039/0.391) and SlopeD (0.030/0.359), respectively. We further control the lagged death rate in columns (4) and (5) and find similar results, though the magnitude decreases slightly. These findings show that there is a causal relationship between the opioid crisis and firm downside risks.[25]

4.2 Alternative identification methods

4.2.1 Propensity score matching (PSM) method

Some firms headquartered in states with PDMPs may be very different from those headquartered in states without PDMPs, making treated firms not comparable to control firms. Therefore, our documented results may be driven by the differences between treated and control firms. To address this concern, we use the propensity score matching (PSM) method to match firms that experienced the implementation of PDMPs with those that did not in our sample, based on key firm characteristics in the year preceding the shock, including Log(Assets), Dividends/net income, Debt/assets, EBIT/assets, CapEx/assets, Book-to-

[24] We remove 7% (311/4,412) of the firms from the main sample in this test.

[25] 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 risks. The IV results reported in Appendix Table B3 are very similar. Note that the first-stage regression in Table B3 is run at firm-level while that in Table 4 is run at county-level.

market, and Returns. We focus on an event window of ten years around the implementation of PDMPs, including five years prior to the adoption and the five years following it. This approach allows us to compare the downside risks of treated firms and control firms with similar characteristics, before and after the introduction of PDMPs.

The results in Panel A of Table 5 show that the treated firms that experience PDMPs have lower downside risks relative to similar peers, supporting the causal impact of exposure to the opioid crisis on firm downside risks. In addition, we see no observable pre-existing trends between the treatment and control groups in Figure 3. To mitigate concerns that PDMPs affect other fundamentals of the treated firms relative to control firms, which can confound documented results, we replace downside risk measures by other firm fundamentals and report the results in Panel B of Table 5. In contrast to the significant and negative impacts of the PDMPs implementation on firm downside risks, we find no significant change in other firm fundamentals after the shocks.

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 (see Cengiz, Dube, Lindner, and Zipperer (2019) and Baker, Larcker, and Wang (2022)). To mitigate these possible biases, we use stacked DiD regressions to check the robustness of our findings. 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 DiD regression on the combined dataset, incorporating dataset-specific firm-cohort and time-cohort fixed effects. The empirical specifications are aligned with those described in Section 4.1. For the stacked DiD regressions, we restrict the treated firms and their control firms to ten years around the PDMPs implementation. We present these regression results in Appendix Table B4 and show that our documented findings are robust to the stacked DiD approach.

4.2.2 Identification strategy using establishment-level data

Again, the implementation of PDMPs at headquarters state might not be highly relevant to a firm's labor force, especially if its employees are widely spread across establishments in different regions. We then aggregate the implementation of PDMPs in a firm's establishment states to the firm-level and conjecture that when PDMPs cover most of a firm's establishment or employees, we would see a significant change in the downside risks.

Specifically, we assign a value of 1 to an establishment-year after the state of this establishment implemented the PDMPs, and zero otherwise. Next, for every year, we calculate the firm-level PDMP coverage using both an equal-weighted average and an employee-weighted average, with the latter weighted by the number of employees at each establishment.

We define a firm as effectively covered by the PDMP when more than 80% of its establishments or employees are in states with PDMP implementation, setting the corresponding pseudo PDMP dummy variable to 1; otherwise, the dummy variable is set to 0. We then re-run the staggered DID regressions with the pseudo PDMP dummy. The results, presented in Table 6, provide supporting evidence that our results are robust to this alternative way to define PDMP implementation. [26]

5 Underlying Channels and Further Discussion

5.1 The opioid crisis, employee productivity, and corporate hiring

We next turn to identify the underlying mechanisms through which the exposure to opioid crisis increases corporate downside risks. Human capital is regarded as the most crucial asset for firms (Zingales (2000)). The opioid crisis could adversely affect employees for at least two main reasons. First, existing employees' health and productivity may be negatively affected by opioids. Employees addicted to opioid drugs have higher rates of absenteeism and

[26] Our results remain consistent when we apply alternative thresholds, including 75% and 67%, to define the effective coverage of PDMP.

presenteeism, lowering productivity. Even if employees are not directly impacted by opioid misuse, they may still be indirectly affected if family members or others in their social networks struggle with addiction, leading to distraction. Second, the opioid crisis could lead to a shortage in the labor market and make it more difficult for firms to find replacements when there is a turnover of employees. As a result, higher exposure to the opioid crisis may result in lower levels of labor productivity and increased labor adjustment costs associated with higher demand in recruiting new employees, leading to heightened downside risks.

To explore this possibility, we first examine how the firm's productivity is affected by its exposure to the opioid crisis. Following Flammer (2015), we define labor productivity as the ratio of sales divided by the number of employees. A higher ratio indicates higher labor productivity.[27] Table 7 column (1) presents the results of whether the opioid crisis lowers labor productivity. We find a significant and negative coefficient, confirming our first conjecture that the exposure to opioid crisis lowers the productivity and the efficiency of existing labor.

We next turn to whether firms respond to increased challenges caused by the opioid crisis. If the productivity of existing labor decreases, a natural response is to recruit more employees. To test this increased hiring hypothesis, we use job posting data from RavenPack Job Analytics. The RavenPack Job Analytics database offers job posting data starting from August 2007. Thus, for the following tests in this section, we limit our sample to firm hiring activities from 2008 to 2021. The database sources hiring information from over 50,000 employers and 200 million job postings all around the world. We obtain comprehensive details on job postings, including company identifiers, job titles, positions, job descriptions, and required skills.

First, we measure a firm's hiring intensity by calculating the industry-adjusted number of job postings in year $t+1$ scaled by its number of employees in year t (Job posting ratio).Column (2) of Table 7 shows that a one-standard-deviation increase in the Death

[27]Flammer (2015) points out that this variable has a highly skewed distribution with extreme values. Therefore, in this regression, we follow Flammer (2015) and winsorize the variables at 5% and 95% levels.

rate is associated with an increase of 0.037 in Job posting ratio, approximately 3% of the variable's standard deviation. This finding is consistent with the increased hiring conjecture. We further investigate how successful the firms are in hiring new employees. If the adverse effect of opioid abuse on the pool of labor, firms may find it challenging to recruit new employees. To test this, we measure the difficulty in recruiting by the Unrecruited ratio, which is the number of job postings remain unfilled one year after the posting, divided by the total number of job postings of each firm each year. We adjust the ratio by the industry-year average. As shown in column (3), we document a positive and significant association between the Death rate and the Unrecruited Ratio. This finding indicates that higher opioid exposure is associated with a greater proportion of job postings that remain unfilled, suggesting heightened hiring frictions for firms operating in areas more severely affected by the opioid crisis.

One solution to overcome the local labor shortage and lower labor productivity caused by the opioid crisis is to automate labor. Therefore, we further categorize posted jobs into two types: non-IT jobs and IT jobs. We classify a job as computer-related if the job position belongs to a computer occupation (SOC code: 15-1200), according to the label by RavenPack.[28] The IT (non-IT) job posting ratio is defined as the industry-adjusted number of computer-related (non-computer-related) positions posted by a firm in year $t+1$ scaled by the number of its employees in year t.

The results in columns (4) and (5) of Table 7 show that both IT and non-IT job posting ratios increase significantly when the companies are headquartered in a county with a higher opioid-related death rate. The finding that firms recruit more IT-related talents to overcome the labor shortage caused by the opioid crisis is consistent with Ouimet, Simintzi, and Ye (2025). However, the significant increase in non-IT job postings shows that not all tasks can be automated. Thus, even with machines or IT technology, firms may suffer labor shortage from the opioid crisis, and downside risks still increase.

[28] SOC is the Standard Occupational Classification system from the U.S. Bureau of Labor Statistics (BLS).

In summary, our findings demonstrate that the opioid crisis significantly hampers employee productivity. Although affected firms seek to address these challenges by hiring new employees, including both IT and non-IT labor, their efforts are impeded by a reduced local labor supply attributable to the crisis. As a result, the opioid epidemic adversely influences the firm and increase corporate downside risk by aggravating labor frictions.

5.2 Impact of labor characteristics

If the opioid crisis increases corporate downside risks by reducing labor productivity, the results are likely to be more pronounced for firms with a high reliance on labor. CDC also reports that the impact of the opioid crisis on employee health is more pronounced for firms in labor-intensive industries, such as mining, construction, and manufacturing.[29] To test this conjecture, we re-examine the effect of opioid exposure on firm downside results for labor-intensive and non-labor intensive firms, respectively. Specifically, we classify a firm's reliance on labor according whether it belongs to a labor-intensive industry, including manufacturing (SIC codes between 2000 and 3999), the construction (SIC codes between 1500 and 1799), and the mining (SIC codes between 1000 and 1499) industries. Firms in labor-intensive industries are classified as the "High Labor Intensity" group, while firms in other industries are classified as the "Low Labor Intensity" group.

Table 8 presents the results. In the "High Labor Intensity" group, we observe that a one-unit increase in Death rate (one more death per 100,000 people) corresponds to an approximate 0.31-percentage-point (t-statistic = 3.88) increase in the NMFIS and a 0.23-percentage-point (t-statistic = 2.92) increase in the SlopeD, and these effects are insignificant for the "Low Labor Intensity" group. We further show that the differences in coefficients between the two groups are statistically significant. Consistent with our argument that the opioid crisis elevates downside risks through its adverse impact on labor, we document a more pronounced effect among labor-intensive industries.

[29] https://www.cdc.gov/niosh/mining/researchprogram/projects/project_OpioidAwarenessTrainingResources.html and https://blogs.cdc.gov/niosh-science-blog/2021/09/14/opioids-in-construction.

We also analyze the role of a firm's labor components on how the opioid crisis influences its downside risks. Not everyone is equally affected by the opioid crisis. For example, males are documented to be more severely affected by the opioid crisis compared to females (CDC (2024)).[30] Specifically, men are more exposed to drug overdoses than women, including opioid abuse. If opioid-exposed firms suffer from low labor productivity and shortage, we expect the effects stronger among firms with more male employees. We split our sample firms into two groups according to the proportion of male employees.[31] Examining the impact of the opioid crisis on downside risks for two subgroups separately, we find, in Appendix Table B5, a stronger result in the group of firms with a higher proportion of male employees. The results, again, are consistent with the channel that the opioid crisis increases firm downside risks by adversely affecting labor productivity.

5.3 Impact of local labor supply

We have shown that as labor productivity is adversely affected by the opioid crisis, firms have the incentive to hire more employees. However, the costs of recruiting new employees vary across regions with different labor market conditions. For example, in regions with a high labor supply, hiring firms face fewer frictions and have more bargaining power against the labor pool. Consequently, firms could quickly replace lower-productivity employees with relatively lower costs. If so, the adverse impact of the opioid crisis can be largely mitigated. As a consequence, we expect that the documented effect should be stronger among firms located in regions with a limited labor supply.

To measure the local labor supply, we define the labor force rate as the ratio of the labor force to the total population of each county. Then we divide the sample firms into two subsamples based on the labor supply at the headquarters county level. For each year, firms

[30] https://nida.nih.gov/research-topics/trends-statistics/overdose-death-rates. The National Institute on Drug Abuse (NIDA) also indicates gender disparities in opioid-related deaths, with men being disproportionately affected and having significantly higher death rates than women.

[31] 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. The proportion of male employees is calculated as (1 − Women Employees).

located in the county with a labor force rate below the median of our sample counties in the same year are classified as "Low Labor Supply," while the others are classified as "High Labor Supply." We repeat our baseline analysis for the two groups, respectively.

The results are presented in Table 9. We find significant results for both groups, but the effect of the opioid crisis on firm downside risks is much stronger among firms headquartered in counties with a lower labor supply. The differences between the two groups are statistically significant for both NMFIS and SlopeD measures. The findings are consistent with our conjecture and further support the labor channel through which the opioid crisis elevates firm downside risks.

5.4 Possible confounding effect of local economic conditions

We have shown that the opioid crisis increases firm downside risks by lowering labor productivity and increasing labor market frictions. However, the worsening local economy due to the opioid crisis could be another possible explanation. For example, when the local economy weakens with the opioid crisis, firms will have less demand, leading to a higher downside risk. This concern becomes more prominent if the major customers are located in the same regions; thus, demand is directly reduced due to the opioid crisis. To rule out that the weakened demand drives our results, we conduct two tests.

First, we classify firms into two groups based on the annual growth rate of GDP (Gross Domestic Product) per capita of the headquarters counties.[32] Specifically, for each year, we split our sample headquarters counties into two groups according to the median of the GDP/capita growth rate. Counties with GDP growth rate above the median are "High GDP Growth" counties, and others are "Low GDP Growth" counties. The firms are then categorized into two subgroups according to the headquarters counties. We re-estimate our baseline regression for each group of firms. As shown in Panel A of Table 10, regardless

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

of the growth of the local economy, firms with higher exposure to the opioid crisis have higher downside risks. These results suggest that local economic conditions are less likely the underlying channel.

Second, we exclude our sample firms if any of the major customers are headquartered in the same county, and repeat our analysis. Major customer data is obtained from Compustat Segment data, which reports customers accounting for more than 10% of revenues.[33] While the sample size shrinks slightly, the magnitude of coefficients in Panel B of Table 10 is very close to the baseline, indicating that our results are not driven by the possibly lower demand of local customers. These two tests suggest that the alternative explanation that the observed increase in firm downside risks is driven by worsening local economic conditions may fail to explain our documented findings.

6 Conclusion

Although several studies have examined the impact of the opioid crisis on firms, our study makes the first attempt to explore the relationship between the opioid crisis and the firm downside risks implied by the option market. Using the opioid crisis as a negative shock to labor productivity and the local labor market, we shed light on a broader question: How does human capital, which is the most important asset of the firm, influence firm risks?

Analyzing a large sample of U.S. public firms from 1999 to 2020, we find a positive association between firm exposure to the opioid crisis, measured by opioid death rates at both headquarters and establishment counties, and downside risks. To establish causality, we exploit the staggered implementation of state-level Prescription Drug Monitoring Programs (PDMPs), which are designed to manage the opioid crisis and are largely exogenous to local firms. Consistent with the panel regression results, We document that the adoption of PDMPs leads to significant reductions in firm downside risks. Moreover, our study explores

[33]Public firms are required by the Financial Accounting Standards Board (FASB) and the SEC to disclose information about major customers who account for at least 10% of their annual total revenues.

the labor channel underlying the negative effect of the opioid crisis on firm downside risks. We find that the opioid crisis reduces firm labor productivity, and firms with larger opioid exposures struggle to hire new employees despite the high corporate demands for human capital. The impact of the opioid crisis on downside risks is also more prominent among firms with higher labor intensity and lower labor supply.

Our study makes contributions to both academic literature and policy implications. Firstly, we highlight the previously underexplored link between public health crises, labor market disruptions, and corporate risks. This insight opens important avenues for further research, particularly concerning other public health crises and their broader economic repercussions. Furthermore, our findings suggest that corporate managers should proactively assess their firms' vulnerabilities to local public health crises and adopt strategies to maintain workforce resilience. Policymakers, on the other hand, should recognize the value of effective public health interventions like PDMPs, which can help better prepare for future shocks, fostering healthier communities and more resilient economies.

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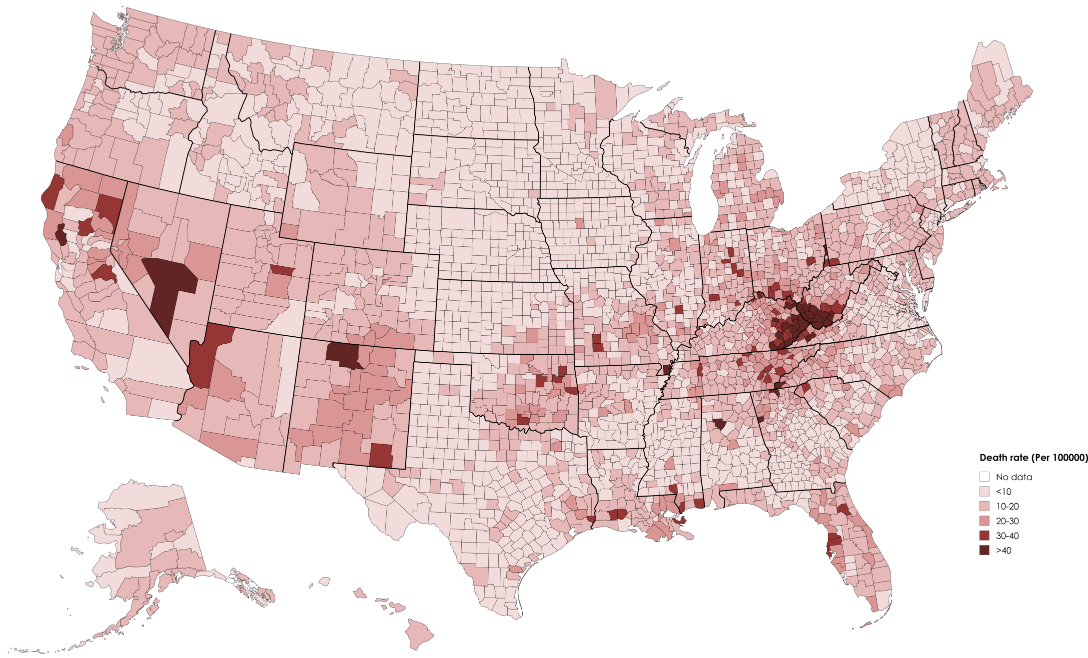
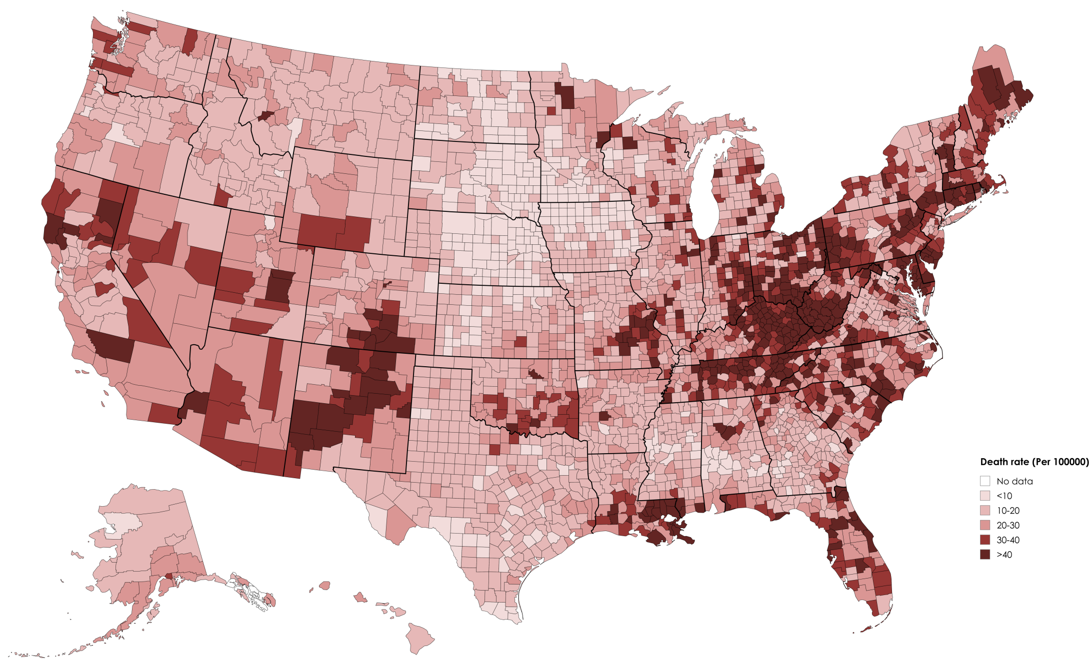
Figure 1. County-level heatmaps for the opioid crisis

This figure illustrates the geographical distribution of the opioid crisis in the U.S. in 2010 and 2020. We present the opioid-related death rate (per 100,000 people) at the county level in a heat map.



(a) County-level heatmap in 2010



(b) County-level heatmap in 2020

Figure 2. The time of PDMPs implementation in different states

This figure illustrates variation in the timing of PDMPs (Prescription Drug Monitoring Programs) implementation across states, with color-coding indicating the year each state adopted its program.

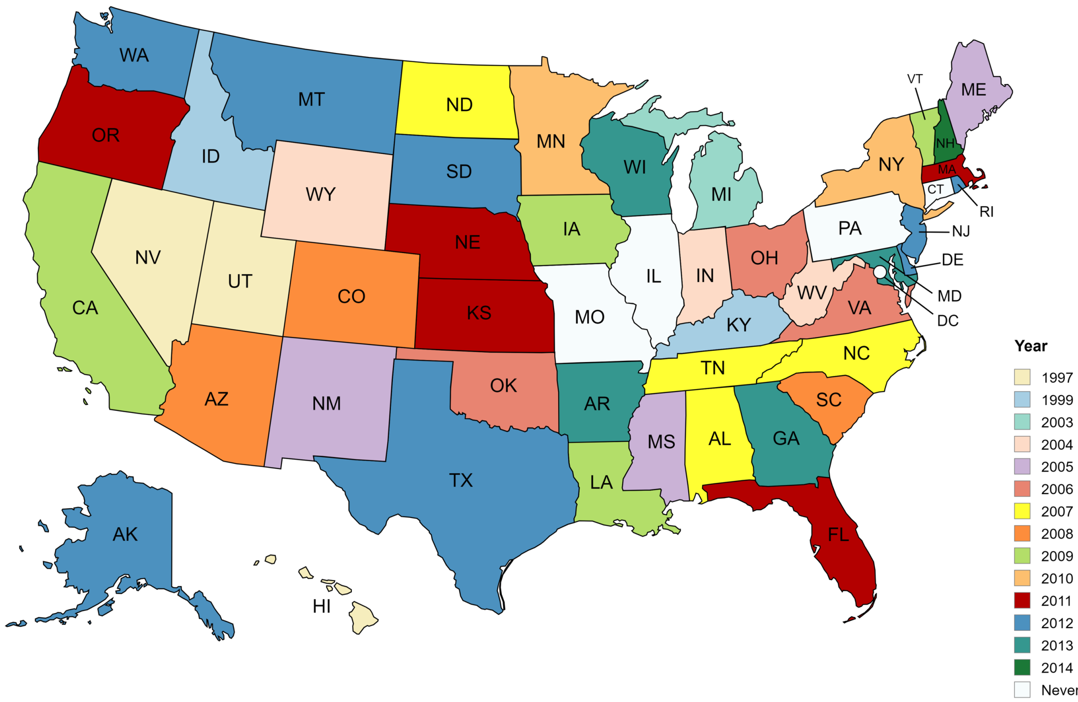
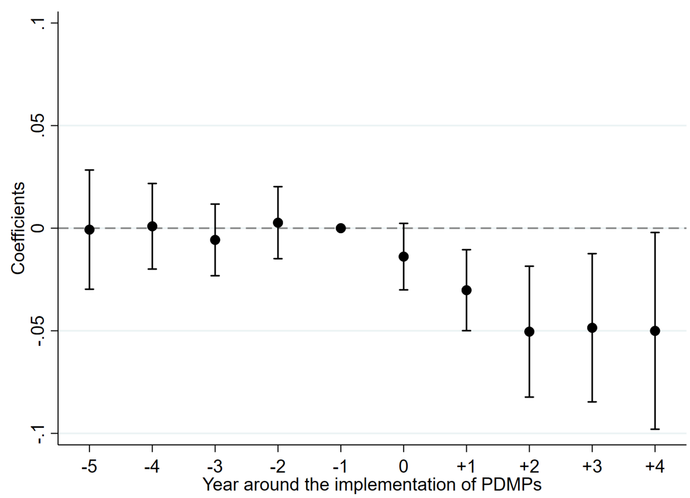
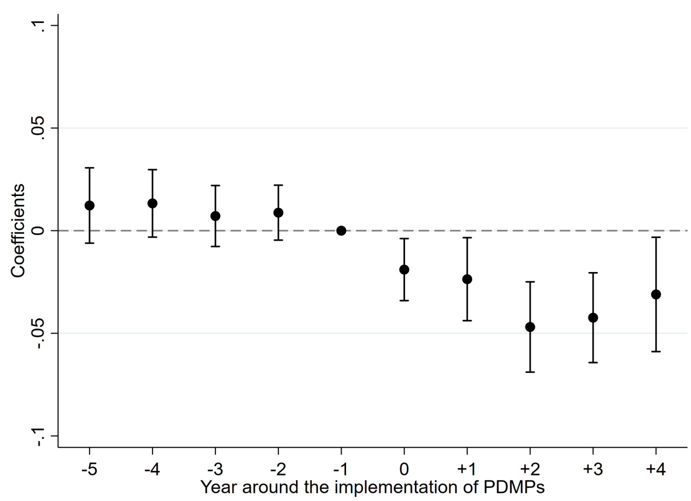


Figure 3. Dynamic effects of PDMPs implementation on downside risks: Evidence from Propensity Score Matching (PSM)

This figure shows the dynamic effects of PDMPs implementation on firm downside risks by using the PSM approach. We plot the regression coefficients of ten years around the PDMPs implementation and their 90% confidence intervals with Year −1 (the year before the implementation of PDMPs) as the benchmark. Treated and control firms are matched according to firm characteristics in Year −1. We include control variables, firm and year fixed effects in Table 2. Standard errors are robust and clustered at the state level. In Figure 3(a), we plot the dynamic effects of PDMPs on NMFIS. In Figure 3(b), we plot the dynamic effects of PDMPs on SlopeD.



(a) NMFIS around the implementation of PDMPs



(b) SlopeD around the implementation of PDMPs

Table 1. Summary statistics

This table summarizes our sample. In Panel A, we report summary statistics for firm-year observations. NMFIS is the negative model-free implied skewness. SlopeD is the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate (per 100,000 people) in the headquarters county. In Panel B, we report summary statistics for county-year observations. Other variables are defined in Appendix A. In Panel C, we calculate correlations among firm characteristics. Our sample spans from 1999 to 2020 and contains no financial or utility firms. All continuous variables are winsorized at 1% and 99% levels.

Variables	Observations	Mean	STD	P25	P50	P75
Panel A: Firm-year level						
NMFIS	35,847	0.367	0.392	0.108	0.355	0.603
SlopeD	35,847	0.376	0.355	0.148	0.260	0.491
Death rate (Per 100,000)	35,847	13.326	8.192	7.959	11.058	16.316
Log(Assets)	35,847	6.897	1.741	5.675	6.841	8.033
Dividends/net income	35,847	0.140	0.455	0.000	0.000	0.180
Debt/assets	35,847	0.225	0.217	0.015	0.191	0.353
EBIT/assets	35,847	0.027	0.205	0.010	0.074	0.126
CapEx/assets	35,847	0.051	0.057	0.017	0.033	0.063
Book-to-market	35,847	0.457	0.394	0.206	0.372	0.616
Returns	35,847	0.167	0.732	-0.235	0.041	0.349
CAPM beta	35,847	1.381	0.845	0.822	1.241	1.775
Volatility	35,847	0.137	0.079	0.081	0.116	0.169
Institutional ownership	35,847	0.692	0.258	0.547	0.757	0.895
Panel B: County-year level						
Death rate (Per 100,000)	6,536	14.673	9.240	8.177	12.287	18.344
Log(Population)	6,536	12.735	1.042	12.028	12.811	13.460
Log(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

Panel C: Correlation matrix												
	NMFIS	SlopeD	Death rate	Log (Assets)	Dividends/ net income	Debt/ assets	EBIT/ assets	CapEx/ assets	Book−to −market	Returns	CAPM beta	Volatility
SlopeD	0.547											
Death rate	0.146	0.287										
Log(Assets)	0.404	0.051	0.095									
Dividends/net income	0.138	0.097	0.061	0.182								
Debt/assets	0.085	0.045	0.135	0.337	0.094							
EBIT/assets	0.308	0.132	-0.001	0.439	0.147	0.038						
CapEx/assets	−0.024	−0.074	−0.049	0.039	−0.008	0.076	0.080					
Book-to-market	−0.173	−0.033	−0.021	0.045	−0.052	−0.121	0.003	0.027				
Returns	0.034	0.014	−0.009	−0.112	−0.041	−0.038	−0.004	−0.066	−0.255			
CAPM beta	−0.182	−0.102	−0.056	−0.186	−0.143	−0.056	−0.214	−0.040	0.042	0.057		
Volatility	−0.355	−0.248	−0.172	−0.470	−0.210	−0.094	−0.422	−0.006	0.024	0.219	0.451	
Institutional ownership	0.339	0.245	0.130	0.376	0.002	0.065	0.347	−0.036	−0.022	−0.045	−0.079	−0.354

Table 2. The effect of the opioid crisis on firm downside risks

We present panel regression results of downside risks on the opioid crisis in Panel A. NMFIS is the negative model-free implied skewness. SlopeD is the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate (per 100,000 people) in the headquarters county. In Panel A, standard errors are clustered at the county level in columns (1) and (2), and double clustered at both the county and year levels in columns (3) and (4). Panel B presents the effect of the opioid crisis on downside risks using alternative measures of firm exposure to the crisis. Death rate_{Raw} is the opioid-related death rate (per 100,000 people) directly obtained from the CDC WONDER database. Death $\text{rate}_{\text{Narrow}}$ is the opioid-related death rate (per 100,000 people) that narrows death causes to natural and semi-synthetic opioids, other synthetic opioids, and heroin. In Panel C, we focus on a subsample of large counties. In columns (1) and (2), the sample is restricted to counties with populations greater than 500,000. In columns (3) and (4), the sample is further narrowed to counties with populations exceeding 1,000,000. In Panel D, we control for some other variables. Death $\text{rate}_{\text{Heart disease}}$ is the death rate from the leading cause of death (per 100,000 people), which is heart disease. Death $\text{rate}_{\text{Top3}}$ includes the death rate from the top three causes of death (per 100,000 people), which are heart disease, cancer, and accidents. Alcohol is the percentage of interviewees identified as heavy drinkers in a state. Standard errors are clustered at the county level in Panels B, C, and D. Other variables are defined in Appendix A. We include firm and year fixed effects in all regressions, and report standard errors in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Baseline results				
Dependent variable	NMFIS (1)	SlopeD (2)	NMFIS (3)	SlopeD (4)
Death rate	0.0025^{***}	0.0020^{***}	0.0025^{***}	0.0020^{***}
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Log(Assets)	0.0755^{***}	0.0085	0.0755^{***}	0.0085
	(0.0057)	(0.0054)	(0.0099)	(0.0074)
Dividends/net income	0.0009	0.0105^{**}	0.0009	0.0105^{**}
	(0.0044)	(0.0042)	(0.0046)	(0.0047)
Debt/assets	-0.1428^{***}	-0.1087^{***}	-0.1428^{***}	-0.1087^{***}
	(0.0195)	(0.0217)	(0.0236)	(0.0226)
EBIT/assets	0.0176	0.0309	0.0176	0.0309
	(0.0189)	(0.0231)	(0.0191)	(0.0229)
CapEx/assets	0.2078^{***}	0.0767	0.2078^{***}	0.0767
	(0.0642)	(0.0541)	(0.0754)	(0.0569)
Book-to-market	-0.1530^{***}	-0.0583^{***}	-0.1530^{***}	-0.0583^{***}
	(0.0093)	(0.0083)	(0.0226)	(0.0133)
Returns	0.0259^{***}	0.0124^{***}	0.0259^{***}	0.0124^{***}
	(0.0034)	(0.0030)	(0.0057)	(0.0045)
CAPM beta	0.0101^{**}	0.0072	0.0101	0.0072
	(0.0051)	(0.0051)	(0.0069)	(0.0056)
Volatility	-0.2232^{***}	-0.2935^{***}	-0.2232^{***}	-0.2935^{***}
	(0.0480)	(0.0372)	(0.0645)	(0.0603)
Institutional ownership	0.1105^{***}	0.1612^{***}	0.1105^{***}	0.1612^{***}
	(0.0203)	(0.0180)	(0.0254)	(0.0280)
Log(Population)	−0.0071	0.0032	−0.0071	0.0032
	(0.0070)	(0.0067)	(0.0074)	(0.0077)
Log(Per capita income)	−0.0118	0.0185	−0.0118	0.0185
	(0.0227)	(0.0210)	(0.0248)	(0.0174)
Population growth	0.1529	0.0119	0.1529	0.0119
	(0.4431)	(0.4320)	(0.4336)	(0.3570)
Employment growth	0.1561	−0.0587	0.1561	−0.0587
	(0.1708)	(0.1596)	(0.1673)	(0.1626)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	County	County	County, Year	County, Year
Observations	35,847	35,847	35,847	35,847
adj-R^2	0.546	0.558	0.546	0.558

Panel B: Alternative measures for the opioid crisis				
Dependent variable	NMFIS (1)	SlopeD (2)	NMFIS (3)	SlopeD (4)
Death rate$_{\text{Raw}}$	0.0024*** (0.0007)	0.0019*** (0.0006)	—	—
Death rate$_{\text{Narrow}}$	—	—	0.0044*** (0.0011)	0.0029*** (0.0011)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	34,879	34,879	31,391	31,391
adj-R^2	0.549	0.559	0.559	0.562

Panel C: Large counties				
	County population$>$ 500k		County population$>$ 1 million	
Dependent variable	NMFIS (1)	SlopeD (2)	NMFIS (3)	SlopeD (4)
Death rate	0.0028*** (0.0008)	0.0022*** (0.0007)	0.0032*** (0.0010)	0.0032*** (0.0010)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	29,024	29,024	18,281	18,281
adj-R^2	0.558	0.559	0.559	0.570

Panel D: Controlling for local health factors (Non-opioid mortality and alcohol use)								
Dependent variable	NMFIS (1)	SlopeD (2)	NMFIS (3)	SlopeD (4)	NMFIS (5)	SlopeD (6)	NMFIS (7)	SlopeD (8)
Death rate	0.0026*** (0.0007)	0.0020*** (0.0006)	0.0027*** (0.0007)	0.0021*** (0.0006)	0.0022*** (0.0007)	0.0017*** (0.0006)	0.0024*** (0.0007)	0.0019*** (0.0007)
Death rate$_{\text{Heart disease}}$	−0.0002 (0.0002)	−0.0001 (0.0001)	—	—	—	—	0.0001 (0.0004)	−0.0000 (0.0003)
Death rate$_{\text{Top3}}$	—	—	−0.0001 (0.0001)	−0.0001 (0.0001)	—	—	−0.0001 (0.0002)	−0.0001 (0.0002)
Alcohol	—	—	—	—	1.0264** (0.4857)	0.7214 (0.5161)	1.0394** (0.4892)	0.7378 (0.5179)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35,845	35,845	35,847	35,847	33,174	33,174	33,174	33,174
adj-R^2	0.546	0.558	0.546	0.558	0.547	0.554	0.547	0.554

Table 3. Alternative measure: Firm-level opioid exposure calculated from establishment counties

This table presents the regression results of the opioid crisis on downside risks using an alternative measure of firm exposure to the opioid crisis. Specifically, we aggregate the opioid death rates of establishment counties to the firm level. Panel A provides summary statistics for this sample. 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 $\text{rate}_{\text{Mean}}$ is the average death rate of all establishments for each firm each year. Death rate_{EW} is computed by weighting each establishment's county opioid death rate by its number of employees, then averaging across all of a firm's establishments. Other variables are defined in Appendix A. Our sample spans from 1999 to 2020 and contains no financial or utility firms. All continuous variables are winsorized at 1% and 99% levels. Panel B shows the panel regression results using the two alternative measures of firm exposure to the opioid crisis. We include firm and year fixed effects in the regressions. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Summary statistics						
Variables	Observation	Mean	STD	P25	P50	P75
NMFIS	21,998	0.436	0.412	0.177	0.442	0.687
SlopeD	21,998	0.431	0.382	0.175	0.293	0.590
Death $\text{rate}_{\text{Mean}}$	21,998	15.018	6.606	10.327	13.246	18.768
Death rate_{EW}	21,998	14.943	6.990	9.986	13.138	18.541
Log(Assets)	21,998	7.252	1.785	6.005	7.220	8.445
Dividends/net income	21,998	0.177	0.494	0.000	0.000	0.267
Debt/assets	21,998	0.234	0.210	0.041	0.206	0.355
EBIT/assets	21,998	0.050	0.183	0.033	0.083	0.134
CapEx/assets	21,998	0.048	0.049	0.017	0.032	0.061
Book-to-market	21,998	0.437	0.366	0.204	0.363	0.592
Returns	21,998	0.151	0.602	-0.189	0.063	0.334
CAPM beta	21,998	1.293	0.741	0.795	1.182	1.658
Volatility	21,998	0.120	0.067	0.074	0.102	0.146
Institutional ownership	21,998	0.718	0.247	0.596	0.783	0.907
Log($\text{Population}_{\text{Mean}}$)	21,998	13.835	0.740	13.495	13.914	14.297
Log(Per capita $\text{income}_{\text{Mean}}$)	21,998	10.790	0.285	10.596	10.766	10.944
Population $\text{growth}_{\text{Mean}}$	21,998	0.009	0.006	0.006	0.009	0.012
Employment $\text{growth}_{\text{Mean}}$	21,998	0.010	0.016	0.005	0.013	0.019
Log($\text{Population}_{\text{EW}}$)	21,998	13.781	0.831	13.371	13.862	14.305
Log(Per capita $\text{income}_{\text{EW}}$)	21,998	10.785	0.305	10.579	10.759	10.954
Population $\text{growth}_{\text{EW}}$	21,998	0.009	0.006	0.005	0.008	0.012
Employment $\text{growth}_{\text{EW}}$	21,998	0.010	0.016	0.004	0.013	0.019

Panel B: Regression results				
Dependent variable	NMFIS (1)	SlopeD (2)	NMFIS (3)	SlopeD (4)
Death rate$_{\text{Mean}}$	0.0035***	0.0025**	—	—
	(0.0012)	(0.0012)		
Death rate$_{\text{EW}}$	—	—	0.0023**	0.0022**
			(0.0011)	(0.0011)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	21,998	21,998	21,998	21,998
adj-R^2	0.542	0.550	0.542	0.550

Table 4. The effect of PDMPs implementation on downside risks: Staggered DiD analysis

This table presents the impact of staggered PDMPs implementation on the opioid crisis and firm downside risks using a staggered difference-in-differences (DiD) analysis. NMFIS is the negative model-free implied skewness. SlopeD is the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate (per 100,000 people) in the headquarters county. In column (1), we examine whether county-level opioid-related death rates drop after a state implemented the PDMPs. PDMP equals one after PDMPs are effective in a county, and zero otherwise. County-level control variables are included. In columns (2)-(5), we examine whether the implementation of PDMPs influences firm downside risks. We exclude firms that relocate across states during our sample. PDMP equals one after PDMPs are effective in a headquarters county, and zero otherwise. Control variables are the same as those in Table 2. We include county and year fixed effects in column (1), and include firm and year fixed effects in other columns. Standard errors are clustered at the state level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	County-level analysis	Firm-level analysis			
Dependent variable	Death rate (1)	NMFIS (2)	SlopeD (3)	NMFIS (4)	SlopeD (5)
PDMP	-1.9656^{**}	-0.0385^{**}	-0.0301^{***}	-0.0385^{**}	-0.0295^{***}
	(0.9676)	(0.0155)	(0.0116)	(0.0157)	(0.0117)
Lagged death rate	—	—	—	0.0012	0.0010
				(0.0009)	(0.0008)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes
County FE	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	6,365	31,479	31,479	30,244	30,244
adj-R^2	0.761	0.549	0.565	0.549	0.564

Table 5. The effect of PDMPs implementation on downside risks: Propensity score matching (PSM) approach

This table presents the impact of staggered PDMPs implementation on firm downside risks using a propensity score matching (PSM) approach. Firms headquartered in states with PDMPs implementation are treated firms and matched with control firms according to characteristics (Log(Assets), Dividends/net income, Debt/assets, Debt/assets, EBIT/assets, CapEx/assets, Book-to-market, and Returns) in the year before PDMPs implementation. Each treated firm is matched with one control firm. We examine a ten-year window around the PDMPs implementation, i.e., [−5, +4], and exclude firms with headquarters relocation. NMFIS is the negative model-free implied skewness. SlopeD is the steepness of the function that relates implied volatility to moneyness. Treat is a dummy variable equal to one for firms headquartered in states with PDMPs implementation, and zero otherwise. Post is a dummy variable equal to one for the years after the PDMPs implementation, and zero otherwise. In Panel A, we present the difference-in-differences regression (DiD) estimates for firm downside risks. In Panel B, we present the difference-in-differences (DiD) regression estimates for other possible firm outcome variables. We include the control variables from Table 2 and firm and year fixed effects in the regressions. Standard errors are clustered at the state level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: The effect of PDMPs on firm downside risks

Dependent variable	NMFIS (1)	SlopeD (2)
Treat×Post	-0.0327^{**}	-0.0421^{***}
	(0.0149)	(0.0118)
Post	0.0034	0.0123
	(0.0112)	(0.0115)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	15,005	15,005
adj-R^2	0.556	0.544

Panel B: The effect of PDMPs on other outcome variables

Dependent variable	Log(Assets) (1)	Dividends /net income (2)	Debt /assets (3)	EBIT /assets (4)	CapEx /assets (5)	Book-to -market (6)	Returns (7)
Treat×Post	0.0116	-0.0097	-0.0015	-0.0018	-0.0019	-0.0068	-0.0006
	(0.0175)	(0.0185)	(0.0072)	(0.0071)	(0.0014)	(0.0208)	(0.0285)
Post	0.0145	-0.0176	0.0059	-0.0002	0.0018	0.0204^{**}	-0.0274^{*}
	(0.0134)	(0.0217)	(0.0049)	(0.0037)	(0.0012)	(0.0096)	(0.0161)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,005	15,005	15,005	15,005	15,005	15,005	15,005
adj-R^2	0.959	0.305	0.792	0.719	0.722	0.560	0.172

Table 6. The effect of PDMPs implementation on downside risks: Aggregating shocks from firm establishments

This table presents alternative measures for the PDMPs implementation on downside risks, based on firm establishment-level data. NMFIS is the negative model-free implied skewness. SlopeD measures the steepness of the function that relates implied volatility to moneyness. $\text{PDMP}_{\text{Mean}}$ equals one if more than 80% of a firm's establishments are located in counties implemented the PDMPs in a given year, and zero otherwise. PDMP_{EW} equals one if more than 80% of employees of a firm work in establishments located in counties implemented the PDMPs in a given year, and zero otherwise. We include firm and year fixed effects in the regressions. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	NMFIS (1)	SlopeD (2)	NMFIS (3)	SlopeD (4)
$\text{PDMP}_{\text{Mean}}$	-0.0362^{***}	-0.0388^{***}	—	—
	(0.0112)	(0.0112)		
PDMP_{EW}	—	—	-0.0239^{**}	-0.0211^{*}
			(0.0111)	(0.0111)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	21,998	21,998	21,998	21,998
adj-R^2	0.543	0.551	0.542	0.550

Table 7. The opioid crisis, employee productivity, and corporate hiring

This table presents panel regression results of the opioid crisis on firm labor productivity and hiring behavior. Labor productivity is the ratio of sales to the number of employees in year t. Death rate is the opioid-related death rate (per 100,000 people) in the headquarters county. Job posting ratio is the industry-adjusted number of jobs posted by a firm within the year $t+1$ divided by the number of employees in year t. Unrecruited ratio is the number of jobs not filled one year after posting divided by the total number of jobs of each firm each year, adjusted for industry-year average. Non-IT job posting ratio is the industry-adjusted number of non-computer occupation jobs posted by a firm within the year $t+1$ divided by the number of employees in year t. IT job posting ratio is the industry-adjusted number of jobs related to computer occupations posted by a firm within the year $t+1$ divided by the number of employees in year t. We include firm and year fixed effects in the regressions. Standard errors are clustered at the county level, and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	Labor productivity (1)	Job posting ratio (2)	Unrecruited ratio (3)	Non-IT job posting ratio (4)	IT job posting ratio (5)
Death rate	-1.1612^{**}	0.0039^{***}	0.0006^{**}	0.0035^{***}	0.0004^{**}
	(0.4844)	(0.0013)	(0.0003)	(0.0012)	(0.0002)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	35,846	15,602	13,933	15,602	15,602
adj-R^2	0.872	0.795	0.298	0.804	0.793

Table 8. Cross-sectional tests on the role of labor intensity

This table presents the effect of the opioid crisis on firm downside risks conditional on whether a firm belongs to labor-intensive industries. NMFIS is the negative model-free implied skewness. SlopeD is the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate (per 100,000 people) in the headquarters county. Firms in manufacturing, construction, and mining industries are categorized as "High Labor Intensity," while firms in other industries are categorized as "Low Labor Intensity." We re-run our baseline panel regressions for the two sub-groups, respectively. We include firm and year fixed effects in the regressions. Standard errors are clustered at the county level and are reported in parentheses. Coefficient differences and the statistical significance are reported in the bottom two rows. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	NMFIS		SlopeD	
	High Labor Intensity (1)	Low Labor Intensity (2)	High Labor Intensity (3)	Low Labor Intensity (4)
Death rate	0.0031***	0.0016	0.0023***	0.0010
	(0.0008)	(0.0010)	(0.0008)	(0.0009)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	21,576	14,271	21,576	14,271
adj-R^2	0.553	0.541	0.565	0.553
Difference (Low−High)	0.0015***		0.0013***	
p-value	(0.0000)		(0.0000)	

Table 9. Cross-sectional tests on the role of local labor supply

This table presents the effect of the opioid crisis on firm downside risks conditional on the labor supply of the firm headquarters county. NMFIS is the negative model-free implied skewness. SlopeD is the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate (per 100,000 people) in the headquarters county. A county's labor supply is measured by the labor force rate. For each year, we classify our sample counties according to the median of labor supply into two groups. Firms in counties with high labor supply are labeled as "High Labor Supply" firms, and other firms are labeled as "Low Labor Supply" firms. We re-run our baseline panel regressions for the two sub-groups, respectively. We include firm and year fixed effects in the regressions. Standard errors are clustered at the county level and are reported in parentheses. Coefficient differences and the statistical significance are reported in the bottom two rows. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	NMFIS		SlopeD	
	Low Labor Supply (1)	High Labor Supply (2)	Low Labor Supply (3)	High Labor Supply (4)
Death rate	0.0037***	0.0021***	0.0027***	0.0015*
	(0.0011)	(0.0008)	(0.0009)	(0.0008)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	15,882	19,959	15,882	19,959
adj-R^2	0.540	0.565	0.565	0.568
Difference (Low−High)	0.0016***		0.0012***	
p-value	(0.0000)		(0.0000)	

Table 10. Local economic growth and local major customers

Panel A presents the effect of the opioid crisis on firm downside risks conditional on local economic growth. Counties are classified into two groups according to the growth rate of GDP per capita. Firms located in a county with a growth rate of GDP per capita below the median are categorized as "Low GDP Growth," while firms located in a county with a growth rate of GDP per capita above the median are categorized as "High GDP Growth." We re-run our baseline panel regressions for the two sub-groups, respectively. Standard errors are clustered at the county level. Coefficient differences and the statistical significance are reported in the bottom two rows. In Panel B, we exclude firms with major customers in the same county. Standard errors are clustered at the county level in columns (1) and (2), and are clustered at the county and year level in columns (3) and (4). We include firm and year fixed effects in all the regressions, and standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: The effect of the local economic conditions

Dependent variable	NMFIS		SlopeD	
	Low GDP Growth (1)	High GDP Growth (2)	Low GDP Growth (3)	High GDP Growth (4)
Death rate	0.0027^{***}	0.0022^{**}	0.0019^{**}	0.0015^{**}
	(0.0010)	(0.0008)	(0.0009)	(0.0007)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	13,856	18,028	13,856	18,028
adj-R^2	0.536	0.567	0.561	0.564
Difference (Low−High)	0.0006		0.0003	
p-value	(0.2300)		(0.2900)	

Panel B: Excluding firms with local major customers

Dependent variable	NMFIS (1)	SlopeD (2)	NMFIS (3)	SlopeD (4)
Death rate	0.0022^{***}	0.0018^{***}	0.0022^{***}	0.0018^{***}
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	County	County	County, Year	County, Year
Observations	34,874	34,874	34,874	34,874
adj-R^2	0.545	0.558	0.545	0.558

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 the yearly level (average of daily values), thus a higher value indicates a higher downside 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 the yearly level (average of daily values). A higher value indicates a higher downside 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)	Log(Assets) is the logarithm of total assets at the end of the year.	Compustat
Dividends/net income	Dividends/net income is dividends at the end of the year divided by net income at the end of the year.	Compustat
Debt/assets	Debt/assets is the sum of the book value of long-term debt and the book value of current liabilities at the end of the year divided by total assets at the end of the year.	Compustat
EBIT/assets	EBIT/assets is earnings before interest and taxes divided by total assets at the end of the year.	Compustat
CapEx/assets	CapEx/assets is capital expenditures at the end of the year divided by total assets at the end of the year.	Compustat
Book-to-market	Book-to-market is the difference between common equity and preferred stock capital at the end of the year divided by the equity market value at the end of the year.	Compustat
Returns	Returns is the stock price at the end of the year divided by the stock price at the end of the previous year, minus 1.	Compustat, CRSP
CAPM beta	CAPM beta is the sensitivity of monthly stock excess returns to monthly market excess returns. The variable is computed for each month with a rolling window of 60 months. For each firm, the variable corresponds to the coefficient on market return. We use average values each year.	Kenneth French's Data Library, CRSP

Volatility	Volatility is the standard deviation of monthly stock returns, computed for each month with a rolling window of the past 12 months. We use average values each year.	CRSP
Institutional ownership	Institutional ownership is the fraction of outstanding shares owned by institutional investors at the end of the year.	Thomson-Reuters
Log(Population$_{\text{Mean}}$)	Log(Population$_{\text{Mean}}$) is the log of the average population of all establishments for each firm each year.	Bureau of Economic Analysis(BEA), YTS
Log(Per capita income$_{\text{Mean}}$)	Log(Per capita income$_{\text{Mean}}$) is the log of the average per capita income of all establishments for each firm each year.	Bureau of Economic Analysis (BEA), YTS
Population growth$_{\text{Mean}}$	Population growth$_{\text{Mean}}$ is the average population growth of all establishments for each firm each year.	Bureau of Economic Analysis (BEA), YTS
Employment growth$_{\text{Mean}}$	Employment growth$_{\text{Mean}}$ is the average employment growth of all establishments for each firm each year.	Bureau of Labor Statistics (BLS), YTS
Log(Population$_{\text{EW}}$)	Log(Population$_{\text{EW}}$) is computed as the log of the weighted average population for each firm based on the proportion of employees in each establishment.	Bureau of Economic Analysis (BEA), YTS
Log(Per capita income$_{\text{EW}}$)	Log(Per capita income$_{\text{EW}}$) is computed as the log of the weighted average of per capita income for each firm based on the proportion of employees in each establishment.	Bureau of Economic Analysis (BEA), YTS
Population growth$_{\text{EW}}$	Population growth$_{\text{EW}}$ 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$_{\text{EW}}$	Employment growth$_{\text{EW}}$ 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
County-level controls		
Log(Population)	Log(Population) is the logarithm of the population number of each county for each year.	Bureau of Economic Analysis (BEA)
Log(Per capita income)	Log(Per capita income) is the logarithm of the average income earned per person of each county for each year.	Bureau of Economic Analysis (BEA)
Population growth	Population growth is the population growth rate of each county for each year.	Bureau of Economic Analysis (BEA)
Employment growth	Employment growth is the employment growth rate of each county for each year.	Bureau of Labor Statistics (BLS)

Other variables		
Labor productivity	Labor productivity is the ratio of sales (in millions) to the number of employees (in thousands) for each firm in each year.	CRSP, Compustat
Job posting ratio	Job posting ratio is the industry-adjusted number of jobs posted by a firm within the year t+1 divided by the number of employees in year t.	Compustat, RavenPack Job Analytics
Unrecruited ratio	Unrecruited ratio is the number of jobs not filled one year after posting divided by the total number of jobs of each firm, adjusted for industry-year average.	Compustat, RavenPack Job Analytics
Non-IT job posting ratio	Non-IT job posting ratio is the industry-adjusted number of non-computer occupation jobs posted by a firm within the year t+1 divided by the number of employees in year t.	Compustat, RavenPack Job Analytics
IT job posting ratio	IT job posting ratio is the industry-adjusted number of jobs related to computer occupations posted by a firm within the year t+1 divided by the number of employees in year t.	Compustat, RavenPack Job Analytics
Labor force rate	Labor force rate is the ratio of the labor force over the total population of each county.	Bureau of Labor Statistics (BLS)
Death rate$_{\text{Mean}}$	Death rate$_{\text{Mean}}$ is the average death rate of all establishments for each firm each year.	CDC, YTS
Death rate$_{\text{EW}}$	Death rate$_{\text{EW}}$ is computed as the weighted average death rate for each firm based on the proportion of employees in each establishment.	CDC, YTS
Death rate$_{\text{Raw}}$	Death rate$_{\text{Raw}}$ is the opioid-related death rate directly obtained from the CDC WONDER database.	CDC
Death rate$_{\text{Narrow}}$	Death rate$_{\text{Narrow}}$ is the opioid-related death rate that restricts multiple causes to natural and semi-synthetic opioids, other synthetic opioids, and heroin.	CDC
Death rate$_{\text{Adults}}$	Death rate$_{\text{Adults}}$ is the opioid-related death rate that restricts people to working-aged adults (aged 25–64 years).	CDC
Death rate$_{\text{Robust}}$	Death rate$_{\text{Robust}}$ 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$_{\text{Sub}}$	Death rate$_{\text{Sub}}$ is the opioid-related death rate that excludes deaths related to intentional self-poisoning by drugs (ICD-10 codes: X60-X64).	CDC
Death rate$_{\text{Heart disease}}$	Death rate$_{\text{Heart disease}}$ is the death rate from the leading cause of death (per 100,000 people), which is heart disease.	CDC
Death rate$_{\text{Top3}}$	Death rate$_{\text{Top3}}$ is the death rate from the top three causes of death (per 100,000 people), which are heart disease, cancer, and accidents.	CDC
Death rate$_{\text{All}}$	Death rate$_{\text{All}}$ is the death rate of all the causes (per 100,000 people) in the headquarters county.	CDC

Other variables		
PDMP	PDMP equals one after PDMPs are effective in a county, and zero otherwise.	Prescription Drug Abuse Policy System
Treat	Treat is a dummy variable equal to one for firms headquartered in states with PDMPs implementation, and zero otherwise.	Prescription Drug Abuse Policy System
Post	Post is a dummy variable equal to one for the years after the PDMPs implementation, and zero otherwise.	Prescription Drug Abuse Policy System
PDMP_{EW}	PDMP_{EW} equals one if 80% of employees from the establishments of a firm are affected by the PDMP shock in a given year, and zero otherwise.	Prescription Drug Abuse Policy System, YTS
$\text{PDMP}_{\text{Mean}}$	$\text{PDMP}_{\text{Mean}}$ equals one if 80% of a firm's establishments are affected by the PDMP shock in a given year, and zero otherwise.	Prescription Drug Abuse Policy System, YTS

Appendix B

Table B1. Robustness and placebo tests

Panel A of this table presents panel regression results of alternative measures for the opioid crisis on downside risks. 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 $\text{rate}_{\text{Adults}}$ is the opioid-related death rate that restricts people to working-aged adults (aged 25–64 years). Death $\text{rate}_{\text{Robust}}$ is the opioid-related death rate that is proxied by dividing drug-related deaths by the county labor force (per 100,000). Death rate_{Sub} is the opioid-related death rate that excludes deaths related to intentional self-poisoning by drugs (ICD-10 codes: X60-X64). Panel B shows firm-level regressions of downside risk on other death reasons. Death $\text{rate}_{\text{Heart disease}}$ is the death rate from the leading cause of death (per 100,000 people), which is heart disease. Death $\text{rate}_{\text{Top3}}$ is the death rate from the top three causes of death (per 100,000 people), which are heart disease, cancer, and accidents. Death rate_{All} is the death rate of all the causes (per 100,000 people) in the headquarters county. We include firm and year fixed effects in the regressions. Standard errors are clustered at the county level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Alternative measures for the opioid crisis						
Dependent variable	NMFIS (1)	SlopeD (2)	NMFIS (3)	SlopeD (4)	NMFIS (5)	SlopeD (6)
Death $\text{rate}_{\text{Adults}}$	0.0014^{***} (0.0004)	0.0012^{***} (0.0004)	—	—	—	—
Death $\text{rate}_{\text{Robust}}$	—	—	0.0012^{***} (0.0003)	0.0010^{***} (0.0003)	—	—
Death rate_{Sub}	—	—	—	—	0.0025^{***} (0.0007)	0.0018^{***} (0.0006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34,661	34,661	34,873	34,873	34,599	34,599
adj-R^2	0.550	0.559	0.549	0.559	0.549	0.559

Panel B: Placebo test						
Dependent variable	NMFIS (1)	SlopeD (2)	NMFIS (3)	SlopeD (4)	NMFIS (5)	SlopeD (6)
Death $\text{rate}_{\text{Heart disease}}$	−0.0002 (0.0002)	−0.0001 (0.0001)	—	—	—	—
Death $\text{rate}_{\text{Top3}}$	—	—	−0.0000 (0.0001)	−0.0000 (0.0001)	—	—
Death rate_{All}	—	—	—	—	−0.0000 (0.0001)	−0.0000 (0.0000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35,845	35,845	35,847	35,847	35,847	35,847
adj-R^2	0.545	0.557	0.545	0.557	0.545	0.557

Table B2. The effect of the opioid crisis on firm downside risks: Excluding healthcare and pharmaceutical firms

This table presents panel regression results of downside risks on the opioid crisis. NMFIS is the negative model-free implied skewness. SlopeD is the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate (per 100,000 people) in the headquarters county. We exclude firms in the healthcare (SIC codes 8011-8099) and pharmaceutical industries (SIC codes 2830-2839) from the main sample. In columns (1) and (2), standard errors are clustered at the county level. In columns (3) and (4), standard errors are clustered at both the county and year levels. We include firm and year fixed effects in the regressions, and report standard errors in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	NMFIS (1)	SlopeD (2)	NMFIS (3)	SlopeD (4)
Death rate	0.0026^{***}	0.0020^{***}	0.0026^{***}	0.0020^{***}
	(0.0007)	(0.0006)	(0.0007)	(0.0007)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	County	County	County, Year	County, Year
Observations	31,491	31,491	31,491	31,491
adj-R^2	0.539	0.555	0.539	0.555

Table B3. The effect of PDMPs implementation on downside risks: Instrumental variable approach

This table presents the two-stage least squares (2SLS) regression results. NMFIS is the negative model-free implied skewness. SlopeD is the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate (per 100,000 people) in the headquarters county. PDMP equals one after PDMPs are effective in a headquarters county, and zero otherwise. We include firm and year fixed effects in the regressions. Standard errors are clustered at the county level and are reported in parentheses. The F-statistics corresponding to the first stage and the statistical significance are reported in the bottom three rows. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	First stage	Second stage	
	Death rate	NMFIS	SlopeD
	(1)	(2)	(3)
PDMP	-2.0664^{***}	—	—
	(0.5814)		
$\widehat{Death\ rate}$	—	0.0186^{***}	0.0146^{**}
		(0.0071)	(0.0064)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	31,479	31,479	31,479
F-statistic	12.63	—	—
p-value	(0.0004)		
Cragg-Donald Wald F-statistic	435.07	—	—

Table B4. The effect of PDMPs implementation on downside risks: Stacked DiD method

This table presents the impact of staggered PDMP implementation on firm downside risks using a stacked DiD method. NMFIS is the negative model-free implied skewness. SlopeD is the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate (per 100,000 people) in the headquarters county. We examine a ten-year window around the PDMPs implementation, and exclude firms with headquarters relocation. In column (1), we examine whether county-level opioid-related death rates drop after a state implemented the PDMPs. PDMP equals one after PDMPs are effective in a county, and zero otherwise. County-level control variables are included. In columns (2)-(3), we examine whether the implementation of PDMPs influences firm downside risks. PDMP equals one after PDMPs are effective in a headquarters county, and zero otherwise. Control variables in Table 2 are included. We include county-cohort and year-cohort fixed effects in column (1), and firm-cohort and year-cohort fixed effects in columns (2) and (3). Standard errors are clustered at the state-cohort level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	County-level analysis	Firm-level analysis	
Dependent variable	Death rate (1)	NMFIS (2)	SlopeD (3)
PDMP	-1.5770^{***}	-0.0353^{***}	-0.0344^{***}
	(0.5768)	(0.0099)	(0.0087)
Controls	Yes	Yes	Yes
Firm-cohort FE	No	Yes	Yes
County-cohort FE	Yes	No	No
Year-cohort FE	Yes	Yes	Yes
Observations	6,992	35,308	35,308
adj-R^2	0.785	0.560	0.565

Table B5. Cross-sectional tests on the role of gender

This table presents the effect of the opioid crisis on firm downside risks conditional on the proportion of male employees. NMFIS is the negative model-free implied skewness. SlopeD is the steepness of the function that relates implied volatility to moneyness. Death rate is the opioid-related death rate (per 100,000 people) in the headquarters county. We obtain the "Women Employees" measure from the Refinitiv database, measured as the number of female employees divided by the total number of a firm's employees. We only keep firm-year observations with the measure available in the following analysis. The proportion of male employees is defined as one minus the proportion of female employees. 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." We re-run our baseline panel regressions for the two sub-groups, respectively. We include firm and year fixed effects in the regressions. Standard errors are clustered at the county level and are reported in parentheses. Coefficient differences and the statistical significance are reported in the bottom two rows. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	NMFIS		SlopeD	
	High Male Proportion (1)	Low Male Proportion (2)	High Male Proportion (3)	Low Male Proportion (4)
Death rate	0.0072^{***}	-0.0017	0.0039^{***}	0.0009
	(0.0018)	(0.0017)	(0.0014)	(0.0016)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,478	1,445	1,478	1,445
adj-R^2	0.653	0.567	0.754	0.754
Difference (High−Low)	0.0089^{***}		0.0030^{**}	
p-value	(0.0000)		(0.0100)	