The Options Market Pricing of Workforce Risk *

Jie Cao, Amit Goyal, Yajing Wang, Xintong Zhan, and Weiming Zhang†

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Abstract

We investigate whether firms' workforce risk is priced in the options market. Using the U.S. opioid crisis as an exogenous shock to human capital, we show that firms with higher workforce uncertainty have higher option-implied downside risk. We exploit a natural experiment and establish causal effects using various difference-in-differences methods. The effects are stronger for firms that are labor-intensive, in low-labor-supply regions, with higher investor attention to labor issues, and without hedging activities. Overall, our findings identify workforce uncertainty as a novel determinant of downside risk, highlighting the important role of human capital in firm risk management and option pricing.

Keywords: Option pricing, option-implied downside risk, human capital, workforce uncertainty

JEL classification: G12, G32, E24, J24, I18

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†Jie (Jay) Cao and Yajing (Stella) Wang are at Hong Kong Polytechnic University School of Accounting and Finance, emails: jie.cao@polyu.edu.hk and yajing.wang@connect.polyu.hk. Amit Goyal is at the University of Lausanne and Swiss Finance Institute, amit.goyal@unil.ch. Xintong (Eunice) Zhan is at Fudan University School of Management, xintongzhan@fudan.edu.cn, corresponding author. Weiming (Elaine) Zhang is at IE University IE Business School, elaine.zhang@ie.edu.

1 Introduction

For investors, the potential for severe losses carries significantly more weight than the prospect of equivalent gains, a fundamental asymmetry that directly shapes corporate valuations and the cost of capital (Roy, 1952; Ang, Chen, and Xing, 2006). To quantify this downside risk, researchers have increasingly turned to the options market. Option-implied measures of downside risk are uniquely powerful because they capture the forward-looking premium that sophisticated investors demand for protection against potential crashes (Bakshi, Kapadia, and Madan, 2003; Ilhan, Sautner, and Vilkov, 2021). While these measures quantify forward-looking downside risk, a fundamental question remains: which firm-specific factors drive this priced downside risk?[1] In this paper, we investigate whether a firm's workforce—one of its most vital asset—is a determinant of this forward-looking downside risk.

As human capital has evolved into the primary cornerstone of corporate value (Zingales, 2000), its stability has become central to firm resilience. Shocks to the workforce do more than just impair daily operations; they disrupt the accumulation of organizational knowledge and diminish a firm's capacity to navigate adverse economic cycles. These disruptions introduce a specific form of left-tail risk. If the workforce-related risk raises the probability or severity of negative cash-flow realization, risk-averse investors will demand a higher premium for protection. Because option traders are sophisticated participants who actively monitor and trade on subtle shifts in firm-specific risks (Easley, O'Hara, and Srinivas, 1998; An, Ang, Bali, and Cakici, 2014), this workforce uncertainty should show up as increased option-implied downside risk.[2]

[1]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.

[2]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 options market because of the higher embedded leverage; thus, information may be incorporated into the options market more efficiently. Furthermore, options market participants primarily consist of institutional investors with a heightened risk sensitivity.

At the same time, it is not ex ante obvious that workforce risk should be priced in the options market for at least two reasons. First, since workforce quality and stability are often opaque to outsiders, investors may lack the granular data necessary to accurately assess these risks. Second, firms may have the operational flexibility to insulate their cash flows from labor shocks. For instance, firms could respond to labor fragility by accelerating capital-labor substitution or adopting labor-augmenting technologies (Autor, Levy, and Murnane, 2003). In such cases, workforce risk would not translate into a higher cost of downside protection. Ultimately, whether the options market identifies and prices this human capital risk remains an open empirical question.

To quantify investors' perceptions of downside risk, we construct two metrics using 30-day equity options. We focus on short-term maturities due to their higher liquidity and sensitivity to new information flows. Our first measure, negative model-free implied skewness (*NMFIS*), captures the asymmetry of the risk-neutral distribution; a higher *NMFIS* indicates a significant shift in probability toward the left tail (Ilhan, Sautner, and Vilkov, 2021). Our second measure, *SlopeD*, calculates the volatility slope of out-of-the-money (OTM) puts (Kelly, Pástor, and Veronesi, 2016). A steeper slope signifies that deep OTM protection has become relatively more expensive, reflecting an increased cost to hedge against tail events. We average daily observations to create a firm-year panel that reflects the options market's aggregate assessment of workforce-related risks.

While option prices provide a clear window into firm downside risk, measuring workforce uncertainty is far more difficult. Ideally, a researcher would use granular data on employee health, skills, and demographics to capture human capital risk. However, such information is rarely available to outside investors or researchers. The U.S. opioid crisis provides a compelling alternative setting, offering a plausibly exogenous shock to workforce uncertainty. This crisis impacts firms' workforce through several distinct channels: diminished labor quality due to absenteeism and presenteeism, productivity losses within affected social networks, elevated labor costs, and tighter local labor markets.[3] To quantify workforce risk (*WFR*), we exploit regional variation in the opioid crisis by calculating the drug-poisoning mortality rate within the county of a firm's headquarters.

We construct a comprehensive panel dataset to investigate the relationship between workforce uncertainty and option-implied downside risk. After excluding financial and utility firms and requiring non-missing variables, we obtain a sample of 35,847 firm-year observations from 4,496 unique public firms from 1999 to 2020.

We begin by providing direct evidence that firms in counties with higher drug-poisoning mortality rates experience significantly lower employee productivity, more job vacancies, and greater hiring frictions. While firms might theoretically mitigate labor shortages through automation, we find that both computer and non-computer job posting ratios increase significantly in high-mortality areas. This suggests that many essential tasks in these firms remain labor-dependent and cannot be easily automated (Autor, Levy, and Murnane, 2003). Together, these findings validate the use of the drug-poisoning death rate as a robust proxy for workforce risk in our subsequent analyses.

We then exploit this shock to human capital to examine whether and to what extent labor market disruptions are reflected in the forward-looking downside risk assessments of sophisticated options market participants. By measuring firm exposure through county-level mortality rates, we capture a source of workforce risk that exhibits substantial cross-sectional variation. Crucially, this regional public health crisis is unlikely to be influenced by individual firm policies, thereby alleviating concerns regarding reverse causality.

In our baseline specifications, a one-standard-deviation increase in *WFR* is associated with an increase of 0.020 in *NMFIS* and 0.016 in *SlopeD*. These effects are economically meaningful, representing approximately 5% of the standard deviation for both risk measures. Importantly, our results remain robust after controlling for other firm-level outcomes

[3] According to a survey by the 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.

previously linked to the opioid crisis, suggesting that the options market prices workforce uncertainty as a distinct risk factor. We further conduct extensive robustness tests and find no material change in our results.

A potential concern is that our results could be driven by deteriorating local economic conditions rather than a direct shock to workforce quality.[4] If the opioid crisis correlates with a weakened regional economy, firms may face heightened downside risk due to a contraction in local demand. We address this alternative explanation through two distinct empirical tests.

First, we examine whether our results are contingent on the broader economic environment by partitioning the sample based on county-level GDP growth. We find that the relationship between *WFR* and option-implied downside risk remains consistent across both high- and low-growth subsamples. This suggests that our findings are not merely a byproduct of contemporaneous macroeconomic fluctuations.

Second, we isolate the labor-supply channel by excluding firms whose primary customers are located within the same headquarters county. By focusing on firms that do not rely on the local population for revenue, we mitigate the concern that our results capture a demand shock rather than a workforce shock. The estimated effects of *WFR* remain quantitatively unchanged in this subsample. Combined with our use of county-level macroeconomic controls and the staggered natural experiment, these results provide strong evidence that the observed increase in downside risk is driven by increased workforce uncertainty.

While our previous tests address observable economic trends, endogeneity remains a concern. For instance, unobserved local factors could simultaneously influence both workforce health and corporate downside risk. To establish causality, we exploit the staggered implementation of state-level Prescription Drug Monitoring Programs (PDMPs) as an exogenous shock to the local opioid supply.[5]

[4]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.

[5]See https://pdaps.org/datasets/pdmp-implementation-dates. PDMPs are state-run electronic databases that track the prescribing and dispensing of controlled substances. By providing physicians with real-time

Using a propensity score matching (PSM) staggered difference-in-differences (DID) design, we find that firms headquartered in states that have implemented PDMPs experience a significant decline in option-implied downside risk. Specifically, after PDMP adoption, the firms' *NMFIS* decreases by 0.033, and *SlopeD* drops by 0.042, equivalent to 9% and 12% of the variables' standard deviations, respectively. The significant reductions in downside risks after headquarters states adopt PDMPs are robust to the use of alternative methods, such as the staggered and stacked DID. Moreover, the parallel trend indicates no observable differences between the treatment and control groups prior to the shock, while downside risk declines in the post-shock period.

To ensure our findings accurately reflect firm-wide workforce disruptions rather than localized headquarters effects, we supplement our primary analysis with an establishment-based approach. First, we construct an employee-weighted measure of workforce risk (*WFR*) by aggregating county-level mortality rates across all of a firm's establishment locations and then run the OLS regression. This more granular measure continues to strongly predict higher option-implied downside risk. Second, we utilize the staggered implementation of PDMPs at the establishment level as an exogenous shock to the local labor supply. We find that firms experience a significant reduction in downside risk when their broader network of operations, not just their headquarters, becomes subject to these opioid-mitigation laws. Taken together, these results confirm that the impact of workforce uncertainty is a pervasive, firm-wide phenomenon that is priced by sophisticated market participants.

Having established a causal relationship between workforce uncertainty and downside risk, we next examine cross-sectional heterogeneity to shed light on the underlying economic mechanism. We find that the impact of *WFR* is significantly amplified for firms with high dependence on human capital and those operating in constrained labor markets. Specifically,

prescription histories, these programs help detect and limit opioid misuse. Prior literature has documented that PDMP adoption effectively reduces regional opioid-related mortality, thereby providing a clean, downward shock to workforce risk.

the effect is more pronounced for labor-intensive firms and those in regions with limited labor supply, where replacing impaired workers is more costly.

Furthermore, we show that the salience of labor issues is a critical driver of options market pricing. The relationship between *WFR* and downside risk is markedly stronger when investor attention is specifically directed toward labor-market conditions, as measured by Google search intensity for workforce-related terms. This suggests that active investor oversight acts as a catalyst for incorporating local labor shocks into option prices. Finally, we find that firms with a sophisticated risk management culture—proxied by the active use of financial derivatives—are better positioned to mitigate these labor-side frictions. Collectively, these results confirm that workforce uncertainty is a distinct operational risk that requires both investor recognition and managerial oversight to be fully reflected and managed.

Our study is related to the growing literature on human capital and its impact on corporate outcomes (Zingales, 2000; Eisfeldt and Papanikolaou, 2013). While prior research has established that labor characteristics, such as mobility, quality, and flexibility, significantly influence firm value and expected returns (Donangelo, 2014; Israelsen and Yonker, 2017; Bae and Kang, 2023), most of this work focuses on the level of human capital. We shift the focus to human capital risk, providing causal evidence on how exogenous shocks to workforce stability translate into heightened downside risk. By doing so, we complement recent studies using granular employee data (Fedyk and Hodson, 2023; Babina, Fedyk, He, and Hodson, 2024) and underscore the necessity of incorporating labor-related uncertainties into the broader corporate risk management framework.

Our paper also naturally contributes to the literature on how firm risks are priced in the options market. A large body of research shows that option-implied measures capture informed trading and incorporate private information about firm fundamentals (Easley, O'Hara, and Srinivas, 1998; Chakravarty, Gulen, and Mayhew, 2004; Cremers and Weinbaum, 2010; Xing, Zhang, and Zhao, 2010; An, Ang, Bali, and Cakici, 2014; Hu, 2014). Recent studies have identified political, earnings, and climate-related uncertainties as key determinants of option-implied measures (Kelly, Pástor, and Veronesi, 2016; Dubinsky, Johannes, Kaeck, and Seeger, 2019; Ilhan, Sautner, and Vilkov, 2021; Cao, Goyal, Zhan, and Zhang, 2026). Our study is the first to establish workforce uncertainty as a novel and significant determinant of option-implied downside risk. We show that sophisticated option traders systematically price the uncertainty associated with human capital, which is an essential but often opaque component of firm risk, broadening the scope of factors understood to influence options market dynamics.

Finally, our paper bridges economics, finance, and public health research by quantifying the corporate consequences of the U.S. opioid epidemic in the options market. While prior work has documented the impact of the crisis on municipal borrowing (Cornaggia, Hund, Nguyen, and Ye, 2022), consumer financing (Jansen, 2023), real estate (Custodio, Cvijanović, and Wiedemann, 2025), and firm innovation and investment (Chen, Huang, Shi, and Yuan, 2024; Cornaggia, Hund, Pisciotta, and Ye, 2025; Ouimet, Simintzi, and Ye, 2025), we provide the first evidence that this public health shock shifts the entire risk distribution of affected firms. Crucially, we show that workforce uncertainty increases downside risk even after controlling for direct operational outcomes. Our findings indicate that option traders look beyond immediate operational disruptions, recognizing that workforce uncertainty fundamentally shifts higher moments of firm value, specifically downside skewness.

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 the baseline results and robustness tests, while Section 4 details our identification strategy and causal evidence. Section 5 explores the underlying economic mechanisms through cross-sectional analyses, and Section 6 concludes.

2 Data and Measures

We collect data on 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 are 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 Downside risk measures

The options 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; An, Ang, Bali, and Cakici, 2014). In this study, we use information from the options 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 Volatility Surface File of Ivy DB OptionMetrics and focus on measures derived from options with a maturity 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 sensitive to shifts in investor information flow and changes in perceived uncertainty and risks.

We construct two option-based measures to identify downside risks, including the negative model-free implied skewness (*NMFIS*) and the implied volatility slope (*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. *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 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.

2.2 Workforce uncertainty measure

We measure a firm's exposure to local labor market instability using the workforce risk (*WFR*) metric. We define *WFR* as the drug-poisoning death rate (adjusted for population) in the county where a firm is headquartered.[6] While mortality is the most extreme outcome,

[6] According to the 10th Revision (ICD-10) codes of the International Classification of Diseases, we attribute deaths with underlying causes including X40-X44 (accidental poisonings by drugs), X60-X64 (inten-

we use the death rate as a high-visibility proxy for the broader prevalence of substance abuse within the local labor pool. This regional health crisis creates significant friction for firms, manifesting in two primary ways. First, it disrupts labor availability and quality, increasing employee absenteeism, presenteeism, and recruitment frictions. Second, firms operating in high-risk areas face elevated non-wage labor costs, including higher healthcare premiums, more frequent workers' compensation claims, and rising disability insurance expenditures.

To protect individual privacy, the CDC suppresses death counts if a county has fewer than ten deaths of an underlying cause in a given year. 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).[7]

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 death causes to specific opioid abuse. However, the truncation issue in this sample would become more severe, given that the number of deaths is more likely to be fewer than

tional self-poisoning by drugs), X85 (assault by drug poisoning), and Y10-Y14 (drug poisoning of undetermined intent) as opioid-related deaths. https://wonder.cdc.gov/mcd-icd10.html.

[7]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 the 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 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.

ten, and there are no estimated data. As a trade-off, we rely on the drug-related death rates as a proxy for opioid-related death rates and acknowledge the limitation of this measure.

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.[8] 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 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' *WFR*, *NMFIS*, *SlopeD*, and firm-level control variables. The mean of the *WFR* is 13.326, showing that on average, 13 out of 100,000 people 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/assets* 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 *WFR* of 14.673 is close to that of firm-year observations,

[8] 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 4.3, we also use the weighted average workforce risk in the counties where the firm's establishments are located as a proxy for a firm's exposure to the workforce uncertainty.

indicating that firms are not concentrated in counties with extremely high or low death rates, allowing us to better estimate the overall impact of workforce uncertainty 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 risk, yet the information contained in the two variables is not exactly the same. *NMFIS* has relatively high correlations with *Log(Assets)* (0.404) and *Institutional ownership* (0.339), which we control for in the regression analysis.

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

2.4 Validating opioid deaths as a measure of workforce uncertainty

We next provide evidence to validate opioid-related death rates as a reliable measure of workforce uncertainty. The opioid crisis impacts firms primarily through two key channels that directly lead to workforce-related disruptions. First, existing employees' health and productivity may be negatively affected by exposure to opioids. Employees addicted to opioid drugs have higher rates of absenteeism and 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 workforce uncertainty.

To test these relationships, we first examine the impact of opioid-related death rates on labor productivity. Following Flammer (2015), we define labor productivity as the ratio of sales to employees, with a higher ratio indicating greater productivity.[9] Column (1) of Table 2 presents our results, showing a significant and negative coefficient on *WFR*. This finding confirms that higher opioid death rates are associated with lower labor productivity, validating our hypothesis that opioid deaths capture disruptions in workforce efficiency.

Next, we investigate the link between opioid death rates and hiring frictions, another critical dimension of workforce uncertainty. Using job posting data from RavenPack Job Analytics,[10] we first measure a firm's hiring intensity by calculating the number of job postings in year $t + 1$ scaled by its number of employees in year t, then adjust this measure at the industry level (*Job posting ratio*). Column (2) of Table 2 shows that a one-standard-deviation increase in the opioid death rate is associated with an increase of 0.032 in the *Job posting ratio*, approximately 3% of the variable's standard deviation.

We further test the relation between the opioid crisis and hiring difficulties. If there is an adverse effect of opioid abuse on the pool of labor, firms may find it challenging to recruit new employees. To test this, we measure recruiting difficulty using the *Unrecruited ratio*, which is the number of job postings remaining unfilled one year after the posting, divided

[9] 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.

[10] 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.

by the total number of job postings for each firm each year. We adjust the ratio by the industry-year average. Column (3) of Table 2 shows a positive and significant association between the opioid 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.

Firms may respond to local labor shortages and declining labor productivity caused by the opioid crisis by increasing their reliance on automation. To analyze this adjustment, we categorize posted jobs into two types: computer-related and non-computer-related jobs. A job is classified as computer-related if the position falls under a computer occupation (SOC code: 15-1200), as labeled by RavenPack. The *Computer job posting ratio* (*Non-computer job posting ratio*) is calculated 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 employees in year t.

The results, presented in columns (4) and (5) of Table 2, show that both computer and non-computer job posting ratios increase significantly for firms headquartered in counties with higher opioid-related death rates. The increase in computer job postings suggests that firms attempt to substitute labor with capital by automating certain tasks. However, the concurrent rise in non-computer job postings indicates that many tasks remain labor-intensive and cannot be automated. These findings align with Autor, Levy, and Murnane (2003), who argue that while firms can invest in technology to automate routine tasks, human labor remains irreplaceable for many non-routine activities. As a result, even with increased automation, firms face persistent workforce challenges, contributing to heightened workforce risk.

In summary, our findings demonstrate that opioid-related death rates capture key aspects of workforce uncertainty, including reduced labor productivity, heightened hiring frictions, and increased labor demand. These results validate our use of opioid-related death rates as a proxy for workforce uncertainty in the subsequent analysis.

3 Baseline Results

3.1 Panel regression: Headquarters exposure to workforce risk

To formally examine the impact of workforce uncertainty on firm downside risks, we begin our analysis with the following panel regression:

$$Downside\ risk_{i,t} = \alpha + \beta \times WFR_{i,t} + Controls_{i,t-1} + Controls_{c,t-1} + FEs + \varepsilon_{i,t}, \qquad (2)$$

where $Downside\ risk_{i,t}$ measures the downside risk for firm i in year t, proxied by *NMFIS* and *SlopeD*. $WFR_{i,t}$ is the workforce uncertainty proxied by 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 the workforce risk is priced in the options market, we expect β to be significantly positive.

Panel A of Table 3 presents the baseline results. Consistent with our hypothesis, β is significantly positive across different specifications, suggesting a positive association between workforce uncertainty and option-implied downside risk. Specifically, in columns (1) and (2), a one-standard-deviation increase in *WFR* (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.[11] These findings are consistent with our conjecture and suggest that workforce risk is priced in the options market.

As mentioned in Section 2.2, the CDC suppresses death counts in cases where a county records fewer than ten deaths in a given year to protect individual privacy, and 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 ensure the robustness and validity of our main results, we consider four alternative measures of firms' exposure to the opioid crisis as proxies for workforce risk. First, we only use the drug-poisoning death rate from the CDC WONDER database as an alternative way to calculate firms' exposure to the opioid crisis to proxy for the workforce risk (WFR_{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 workforce uncertainty. 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 WFR_{Narrow}. Third, we restrict the death rate to working-aged adults (aged 25–64 years), as it better reflects the local workforce quality and labor market frictions (WFR_{Adults}). Fourth, 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 (WFR_{Robust}).

The coefficients on *WFR* reported in Panel B of Table 3 remain significant for all alternative measures. To further mitigate possible bias from suppressed death counts, we restrict our analysis to larger counties, which are unlikely to have suppressed observations.[12] The

[11] 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.

[12] 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 populations exceeding 1,000,000, yielding 18,281 firm-year observations with no missing data.

results of these robustness tests, presented in Panel A of Appendix Table B1, show magnitudes similar to the baseline regression, demonstrating that the NCHS estimated death rate does not systematically bias our findings.

To ensure that our results are not driven by general local health conditions, we include additional county-level health indicators as control variables. Specifically, we control for workforce risk potentially arising from other causes of death, including the leading cause of death (heart disease) and the top three causes of death (heart disease, cancer, and accidents).[13] In addition, we control for the percentage of individuals identified as heavy drinkers within a state ($WFR_{Alcohol}$), as excessive alcohol consumption is another significant public health issue that might influence firm-level risks.[14] Panel C of Table 3 reveals that the coefficient on WFR remains statistically significant after adding these control variables, whereas most of these control variables are statistically insignificant. These results highlight the distinct and non-negligible influence of workforce uncertainty on firm downside risks.

As a complementary test, we perform placebo analyses to examine whether our findings are unique to the opioid crisis as a proxy for workforce uncertainty. 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 rather than opioid-specific workforce disruptions. Consistent with our observations in Panel C of Table 3, none of these alternative health measures exhibits a significant effect on firm downside risk, reinforcing the interpretation that opioid-related workforce risk captures a distinct channel affecting firms' downside exposure.

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

[13]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.

[14]Alcohol data are 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 an upward 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 Panel C of Appendix Table B1 remain similar to the baseline results, providing evidence that our baseline findings are not driven by litigation risk.[15]

As a further robustness check, we control for firm-level outcomes that prior studies document as being negatively impacted by the opioid crisis, to examine whether our results are merely a reflection of these effects. Previous literature documents adverse real effects of the opioid crisis on corporate future sales and employment growth (Ouimet, Simintzi, and Ye, 2025), as well as on firm innovation output and quality (Chen, Huang, Shi, and Yuan, 2024; Cornaggia, Hund, Pisciotta, and Ye, 2025). Specifically, we control for *Sales growth*, *Employee growth*, innovation output, and quality in year $t+1$,[16] and find no material change in our results as shown in Panel D of Table 3.

3.2 Possible confounding effects of local economic conditions

We have shown that workforce risk is priced in the options market. However, a worsening local economy associated with workforce risk may provide an alternative explanation. For example, if workforce uncertainty weakens the local economy, firms will have less demand, which in turn increases downside risk. This concern becomes more pronounced when the major customers are concentrated in the same region, as demand is directly reduced by the local economy. To rule out the possibility that reduced demand drives our results, we conduct two additional tests.

[15] In unreported tests, we examine how exposure to the workforce risk 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, are offset by the litigation risks or the weakened employee productivity.

[16] All four variables are constructed for the following year because prior literature indicates that the opioid crisis impacts firm outcomes in the next year. Patent data are available from Kogan, Papanikolaou, Seru, and Stoffman (2017), with updates extending to 2024 (See https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data).

First, we classify firms into two groups based on the annual growth rate of GDP (Gross Domestic Product) per capita of the headquarters counties.[17] 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 a 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 subgroup. As shown in Panel A of Table 4, firms with higher exposure to the workforce uncertainty have higher downside risks in both high- and low-growth counties. These results suggest that local economic conditions are unlikely to drive our results.

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 are obtained from Compustat Segment data, which reports customers accounting for more than 10% of revenues.[18] While the sample size shrinks slightly, the magnitudes of the coefficients in Panel B of Table 4 remain very similar to those in the baseline, indicating that our results are not driven by potentially lower demand from local customers. These two tests together suggest that the alternative explanation that the observed increase in firm downside risks is driven by worsening local economic conditions is not supported by our findings.

4 Identification Strategy

4.1 Prescription Drug Monitoring Programs

A primary challenge in our empirical analysis is the potential for endogeneity, specifically from omitted variable bias. For instance, deteriorating local economic conditions could simul-

[17] 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.

[18] 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.

taneously increase a firm's downside risk and exacerbate substance abuse within the regional workforce. While we control for county-level macroeconomic indicators, latent local factors may still confound our results. To isolate the causal impact of workforce risk, we exploit the staggered implementation of state-level Prescription Drug Monitoring Programs (PDMPs). These programs serve as exogenous shocks to the local supply of opioids, effectively reducing abuse and mortality rates independent of a firm's performance. Using a staggered difference-in-differences (DID) framework, we test whether the reduction in workforce risk following PDMP adoption leads to a corresponding decrease in firm-level downside risk.

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 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, they 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.[19] 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; 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 workforce risk in our sample, we run the following county-year level regression:

$$WFR_{c,t} = \alpha + \beta \times Treat_s \times Post_{s,t} + Controls_{c,t-1} + FEs + \varepsilon_{c,t}, \quad (3)$$

[19] 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 $Treat_s$ is a dummy variable equal to one for firms headquartered in states s with PDMPs implementation, and zero otherwise. $Post_{s,t}$ is a dummy variable that equals one after the year of adoption of the PDMP for firm i located in state s. $Controls_{c,t-1}$ include county-level *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 county level. As shown in column (1) of Table 5, the coefficient is negative and significant. The effect is substantial, with a decrease in *WFR* 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 firms' opioid exposure and workforce uncertainty.

Some firms headquartered in states with PDMPs may differ significantly 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-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.

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

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

where $Downside\,risk_{i,t}$ is the downside risk, proxied by *NMFIS* or *SlopeD*, for firm i in year t. $Treat_s$ is a dummy variable equal to one for firms headquartered in states s with PDMPs implementation, and zero otherwise. $Post_{s,t}$ is a dummy variable that equals one after the year of adoption of the PDMP for firm i located in state s. We include all control variables from Table 3 and remove firms that relocated their headquarters to other states during our sample period. 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 workforce uncertainty, β should be significantly negative.

The results in the last two columns of Panel A of Table 5 show that treated firms that experience PDMPs have lower downside risks relative to similar peers, supporting the causal impact of workforce uncertainty on firm downside risks. Specifically, after PDMP adoption, the firms' *NMFIS* decreases by 0.033, and *SlopeD* drops by 0.042, equivalent to 9% and 12% of the variables' standard deviations, respectively. We also evaluate the effectiveness of PSM by examining whether the matched variables are balanced across the treatment and control groups. Panel B of Table 5 presents the comparison results between the treatment and control firms, showing that the differences between the two groups are minimal and statistically insignificant after applying the PSM method. Consistent with this evidence, Figure 3 reveals no observable pre-existing trends between the treatment and control groups.

PDMPs differ across states and over time in several regulatory dimensions. To capture this heterogeneity, we follow Martins et al. (2019) and Smith et al. (2019) to construct a PDMP intensity measure based on nine policy features that reflect monitoring, reporting, and data-access provisions of state PDMP programs. Panel A of Appendix Table B2 provides the detailed definitions and coding of these features. Following the coding scheme in the PDAPS database, we collapse the original response categories into ordered categories reflecting increasing levels of monitoring and access. For each feature, we assign a score based on the collapsed categories and compute the average across the nine features to construct a composite PDMP intensity score (*PDMPscore*) at the state-year level. Higher values of *PDMPscore* indicate PDMP programs with more intensive monitoring, more frequent reporting requirements, and broader access to prescription data. We then interact *PDMPscore* with the post-policy indicator to examine whether the effects of the policy vary with PDMP intensity across states. Panel B of Appendix Table B2 presents the results, which suggest that the reduction in corporate downside risk associated with PDMP implementation is stronger in states with higher PDMP intensity.

4.2 Alternative identification methods: Staggered DID and stacked DID

Next, we run the staggered DID regression as a robustness test. The results in Panel A of Appendix Table B3 show that when headquarters states implement PDMPs, firms experience lower downside risk. As a robustness check, we use the implementation of PDMPs as an instrumental variable (IV) for the workforce risk to identify the causal impact of the workforce uncertainty on downside risks. The IV results reported in Appendix Table B4 are very similar.

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 (Cengiz, Dube, Lindner, and Zipperer, 2019; Baker, Larcker, and Wang, 2022). To mitigate potential biases, we use stacked DID regressions to assess 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 implementation of PDMPs. We present these regression results in Panel B of Appendix Table B3 and find that our findings are robust to the stacked DID approach.

4.3 Identification strategy using establishment-level data

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

Establishment-level data are obtained from the Your-economy Time-Series (YTS) database, including establishment location, number of employees, and sales volume.[20] We construct two alternative firm-level measures of the workforce uncertainty based on the counties where the establishments are located, and only include economically important establishments, i.e., those with more than 10 employees.[21] First, we take the average of the establishment-county workforce risk as WFR_{Mean}. Second, we take the employee-number-weighted average of establishment-county workforce risk for a firm and label it as WFR_{EW}.

Panel A of Table 6 reports the summary statistics of this sample, which has 21,998 firm-year observations. Then we rerun our baseline regressions using workforce uncertainty aggregated at the establishment level. As shown in Panel B of Table 6, the results are largely consistent with the baseline results.[22] A one-standard-deviation increase in WFR_{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-

[20] 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)).

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

[22] The reduction in sample size is because not all of our sample firms have a valid establishment record in the YTS database. The results also hold if we construct the workforce risk using establishment sales as weights.

level data more comprehensively capture the overall exposure of firms to the workforce risk, further demonstrating the robustness of our results.

Similarly, the implementation of PDMPs at the 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 PDMP implementation across a firm's establishment states to the firm level and conjecture that when PDMPs cover most of a firm's establishments or employees, we would see a significant change in downside risks. Specifically, we assign a value of one to an establishment-year after the state in which the establishment is located implemented PDMPs, and zero otherwise. Next, for each year, we calculate 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 classify 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 one; otherwise, the dummy variable is set to zero. We then rerun the staggered DID regressions with the pseudo PDMP dummy. The results, presented in Table 7, provide supporting evidence that our results are robust to this alternative definition of firms' exposure to PDMP implementation.[23]

5 Heterogeneity Tests

5.1 The impact of labor characteristics

Given our central finding that workforce risk is priced in the options market, the results are likely to be more pronounced for firms with a high reliance on labor. When labor is a key production input, shocks to employee health, availability, or productivity are more likely to disrupt operations and cash flows, thereby amplifying downside risk. Consistent with this

[23] Our results are unaffected when we apply alternative thresholds, including 75% and 67%, to define the effective coverage of PDMP.

intuition, the 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.[24] To test this conjecture, we re-examine the effect of workforce uncertainty on firm downside performance for labor-intensive and non-labor-intensive firms. Specifically, we classify firms as labor-intensive if they operate in manufacturing (SIC codes between 2000 and 3999), construction (SIC codes between 1500 and 1799), and mining (SIC codes between 1000 and 1499) industries. These firms 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 increase in the *NMFIS* and a 0.23-percentage-point increase in the *SlopeD*, and these effects are insignificant in the "Low Labor Intensity" group. We further show that the differences in coefficients between the two groups are statistically significant (p-value = 0.00). Thus, the effect of workforce uncertainty on the increase in downside risk is more pronounced in labor-intensive industries.

We also analyze how a firm's labor composition shapes the effect of workforce uncertainty on 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).[25] Specifically, men are more exposed to drug overdoses than women, including those from opioid abuse. Therefore, we expect the effects to be stronger among firms with more male employees. We split our sample firms into two groups according to the proportion of male employees.[26] Examining the impact of workforce uncertainty on downside risks for two

[24]https://www.cdc.gov/niosh/bulletin/2025/mining-sud.html and https://blogs.cdc.gov/niosh-science-blog/2021/09/14/opioids-in-construction.

[25]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.

[26]We obtain the "Women Employees" measure from the Refinitiv database, calculated as the number of women employees divided by the total number of company employees. The proportion of male employees is calculated as (1 − Women Employees).

subgroups separately, we find, in Appendix Table B5, a stronger result in the group of firms with a higher proportion of male employees.

5.2 The impact of local labor supply

We have shown that firms have an incentive to hire more employees when they face higher workforce risk. However, the costs of recruiting new employees vary across regions depending on local labor market conditions. For example, in regions with a high labor supply, firms face fewer hiring frictions and have greater bargaining power in the labor market, allowing them to quickly replace lower-productivity employees at relatively lower cost. As a result, the adverse impact of workforce risk can be mitigated. Consequently, we expect our results to be stronger among firms headquartered in regions with lower labor supply.

To capture local labor market conditions, we measure local labor supply using the labor force rate, defined 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 force rates at the headquarters county level. For each year, firms 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 workforce uncertainty on firm downside risks is much stronger among firms headquartered in counties with lower labor supply. The differences between the two groups are statistically significant for both *NMFIS* and *SlopeD* measures.

5.3 The impact of investor attention to labor issues

How workforce risk is priced in the options market depends on how market participants perceive and process such risk. We posit that investor attention to labor-market conditions acts as an information channel, facilitating the incorporation of workforce-related uncertainty into option prices. When attention is high, investors are more likely to monitor and respond to labor market disruptions, leading to a more pronounced pricing of downside risks. Consequently, we expect the relationship between workforce uncertainty and firm-level downside risk to be amplified for firms with higher investor visibility.

To proxy for investor attention to workforce risk, we use the Google search volume index (SVI) from Google Trends for the specific terms "workforce" and "labor." Unlike general searches, this measure specifically targets the intensity of information-seeking behavior regarding labor-market stability.[27] We calculate the annual state-level search intensity for both terms and define our attention measure as their average. Each year, we partition the sample into "High Attention" and "Low Attention" groups based on the median SVI of the firm's headquarters state. We then re-estimate our baseline regressions separately for the two subsamples.

Table 10 presents the subsample regression results. For both *NMFIS* and *SlopeD*, the impact of *WFR* is significantly stronger in the "High Attention" group. Specifically, the coefficient for *WFR* in the "High Attention" subsample is positive and statistically significant (0.0040 for *NMFIS* and 0.0024 for *SlopeD*), whereas the coefficients in the "Low Attention" group are markedly smaller. The differences in coefficients between these two groups are statistically significant, confirming that investor attention facilitates the efficient integration of workforce-related shocks.

5.4 The impact of corporate hedging activities

A firm's use of derivatives for financial risk hedging often reflects a broader risk management culture and greater operational maturity. Such firms typically maintain more systematic internal controls, adopt forward-looking planning mechanisms, and demonstrate stronger resilience in the face of diverse risks and uncertainties. Building on this rationale, we hy-

[27] The sample period for our analysis begins in 2004 due to the availability of data from Google Trends (https://trends.google.com/trends/), which provides data starting from 2004. The index ranges from 0 to 100. For each year, we obtain state-level Google search volume indexes for the terms "workforce" and "labor" separately and define the investor attention measure as the average of the two.

pothesize that firms engaged in hedging activities are also better positioned to manage and mitigate the workforce-related risk. As a result, we expect the sensitivity of a firm's option-implied downside risk to workforce uncertainty to be weaker for firms that engage in hedging activities than for non-hedgers.

To test this hypothesis, we classify firms into "Hedgers" and "Non-hedgers" based on reported gains/losses on derivatives and hedging in their income statement data from Compustat. Firms reporting nonzero gains/losses on derivatives are labeled as "Hedger" firms, and other firms are labeled as "Non-hedger" firms. We then estimate our regression specifications separately for the two groups, and report the results in Table 11. The findings reveal that workforce uncertainty is positively and significantly associated with downside risk among "Non-hedger" firms, whereas the coefficient for "Hedger" firms is insignificant. Moreover, the difference between the two groups is statistically significant. This supports the view that the impact of workforce uncertainty on firms' downside risk is significantly stronger for firms that do not engage in active hedging.

6 Conclusion

While a growing body of literature recognizes human capital as a cornerstone of corporate value, our study is the first to demonstrate that workforce risk is priced in the options market. By exploiting the U.S. opioid crisis as a significant and exogenous shock to labor productivity and the local labor market, we shed light on a fundamental question: How does human capital, which is the most vital asset of the firm, shape its forward-looking risk profile?

Using a comprehensive sample of U.S. public firms from 1999 to 2020, we find a positive association between firm exposure to workforce uncertainty, measured by opioid death rates at both headquarters and establishment counties, and option-implied 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 workforce uncertainty and downside risks. Furthermore, our cross-sectional tests reveal that this effect is concentrated in firms with high labor dependency, those operating in constrained labor markets, and those where investor attention is specifically focused on workforce issues. Conversely, we find that a sophisticated risk management culture, proxied by financial hedging, acts as a critical buffer against these labor-side frictions.

Through the lens of the options market, our research provides novel evidence on how public health crises threaten business resilience. These findings underscore that workforce health is not an external factor to be ignored by financial models; rather, it is a core operational risk that sophisticated market participants actively price. By quantifying the financial costs of workforce uncertainty, our study highlights that investing in human capital is not merely a social responsibility—it is a financial imperative and a foundation for long-term firm sustainability.

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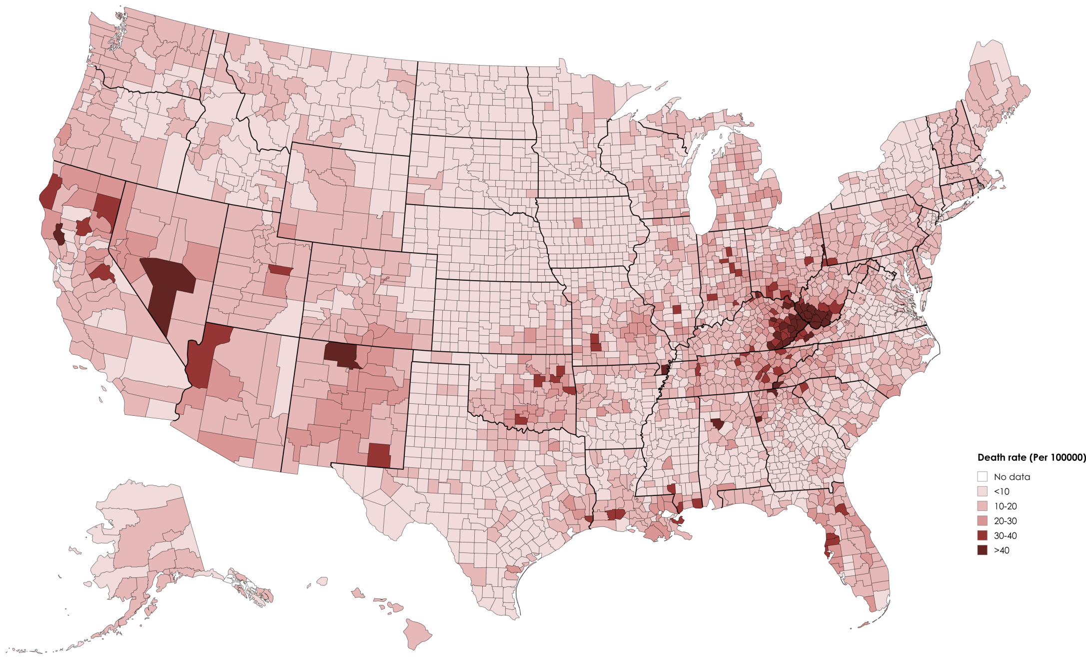
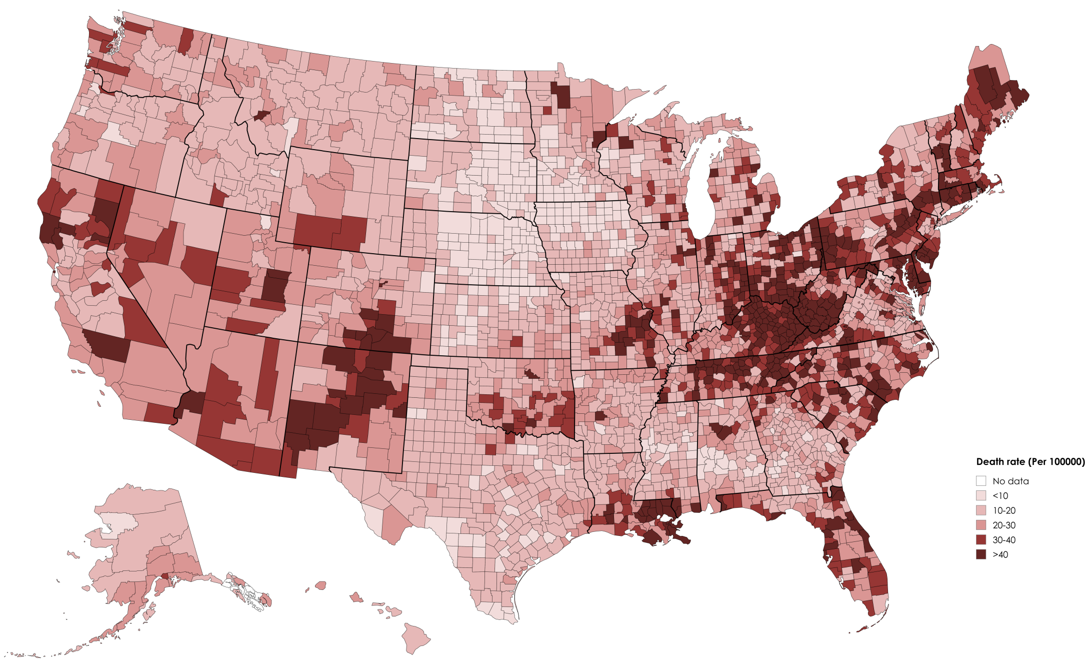
Figure 1. County-level heatmap for the workforce risk

This figure illustrates a geographical distribution of the workforce risk in the U.S. in 2010 and 2020. We present the workforce uncertainty 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 the variation in the timing of PDMPs (Prescription Drug Monitoring Programs) implementation across states, with color-coding indicating the year each state adopted its program.

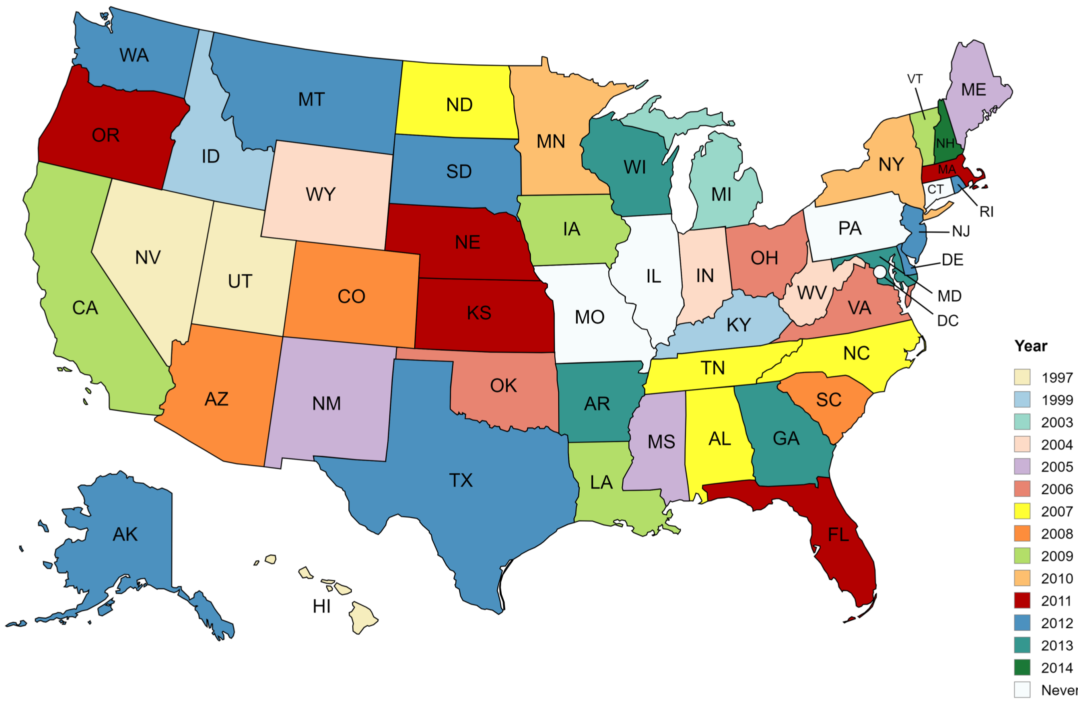
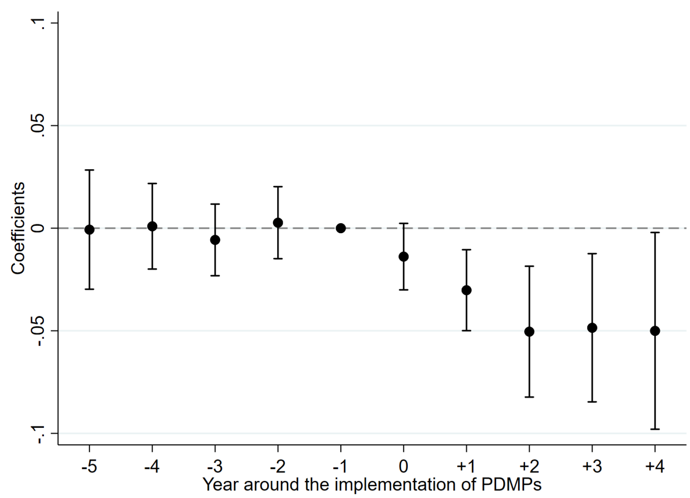
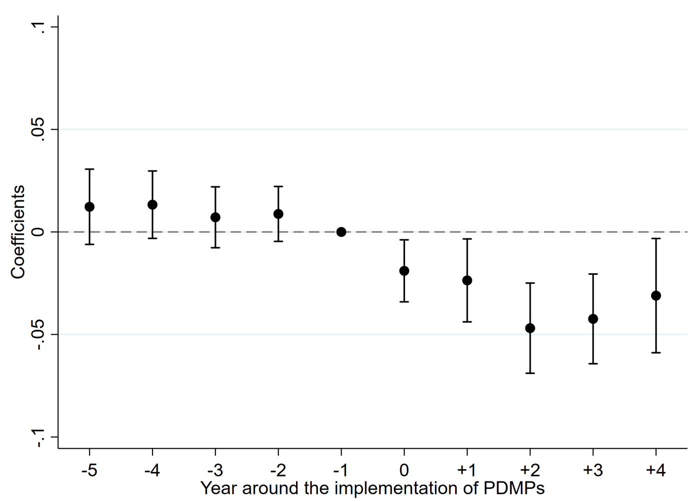


Figure 3. Dynamic effects of PDMPs implementation on downside risk: Evidence from Propensity Score Matching (PSM)

This figure shows the dynamic effects of PDMPs implementation on firm downside risk 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 3. 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* represents the negative model-free implied skewness. *SlopeD* measures the steepness of the function that relates implied volatility to moneyness. *WFR* is the firm's workforce uncertainty represented by the opioid death rate 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 excludes financial and utility firms. All continuous variables are winsorized at the 1% and 99% levels.

Variables	Observation	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
WFR	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						
WFR	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	WFR	Log (Assets)	Dividends /net income	Debt /assets	EBIT /assets	CapEx /assets	Book-to -market	Returns	CAPM beta	Volatility
SlopeD	0.547											
WFR	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. Validating opioid death rate as a measure of workforce uncertainty

This table presents panel regression results of the workforce uncertainty measure proxied by 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*. *WFR* 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-computer 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*. *Computer 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 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-computer job posting ratio (4)	Computer job posting ratio (5)
WFR	−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 3. The effect of workforce uncertainty on firm option-implied downside risk

We present panel regression results of downside risk on workforce uncertainty in Panel A. *NMFIS* represents the negative model-free implied skewness. *SlopeD* measures the steepness of the function that relates implied volatility to moneyness. *WFR* is the workforce uncertainty 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 workforce uncertainty on downside risks using alternative measures of firm exposure to the crisis. WFR_{Raw}, WFR_{Narrow}, WFR_{Adults}, and WFR_{Robust} are alternative measures of workforce uncertainty. Panel C controls for local health factors. WFR_{Heart}, WFR_{Top3}, and $WFR_{Alcohol}$ are additional controls. Panel D controls existing firm outcomes. Standard errors are clustered at the county level. We include firm and year fixed effects in all regressions. *, **, 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)
WFR	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 workforce uncertainty								
Dependent variable	NMFIS (1)	SlopeD (2)	NMFIS (3)	SlopeD (4)	NMFIS (5)	SlopeD (6)	NMFIS (7)	SlopeD (8)
WFR_{Raw}	0.0024***	0.0019***	—	—	—	—	—	—
	(0.0007)	(0.0006)						
WFR_{Narrow}	—	—	0.0044***	0.0029***	—	—	—	—
			(0.0011)	(0.0011)				
WFR_{Adults}	—	—	—	—	0.0014***	0.0012***	—	—
					(0.0004)	(0.0004)		
WFR_{Robust}	—	—	—	—	—	—	0.0012***	0.0010***
							(0.0003)	(0.0003)
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	34,879	34,879	31,391	31,391	34,661	34,661	34,873	34,873
adj-R^2	0.546	0.558	0.546	0.558	0.550	0.559	0.549	0.559

Panel C: 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)
WFR	0.0026***	0.0020***	0.0027***	0.0021***	0.0022***	0.0017***	0.0024***	0.0019***
	(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0007)
WFR_{Heart}	−0.0002	−0.0001	—	—	—	—	0.0001	−0.0000
	(0.0002)	(0.0001)					(0.0004)	(0.0003)
WFR_{Top3}	—	—	−0.0001	−0.0001	—	—	−0.0001	−0.0001
			(0.0001)	(0.0001)			(0.0002)	(0.0002)
$WFR_{Alcohol}$	—	—	—	—	1.0264**	0.7214	1.0394**	0.7378
					(0.4857)	(0.5161)	(0.4892)	(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

Panel D: Controlling existing outcomes affected by WFR						
Dependent variable	NMFIS (1)	SlopeD (2)	NMFIS (3)	SlopeD (4)	NMFIS (5)	SlopeD (6)
WFR	0.0024***	0.0019***	0.0029***	0.0018***	0.0029***	0.0018***
	(0.0006)	(0.0006)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Sales growth	0.0198**	0.0124***	—	—	0.0147***	0.0128***
	(0.0048)	(0.0029)			(0.0048)	(0.0034)
Employee growth	0.0696***	0.0237***	—	—	0.0837***	0.0319***
	(0.0109)	(0.0072)			(0.0134)	(0.0085)
Log(1+patent)	—	—	−0.0123	−0.0101	−0.0107	−0.0093
			(0.0098)	(0.0085)	(0.0098)	(0.0085)
Log(1+citation)	—	—	0.0070	−0.0040	0.0057	−0.0045
			(0.0059)	(0.0052)	(0.0058)	(0.0052)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,679	32,679	15,351	15,351	15,351	15,351
adj-R^2	0.550	0.559	0.549	0.559	0.549	0.559

Table 4. Local economic growth and local major customers

Panel A presents the effect of the workforce uncertainty on firm downside risk conditional on local economic growth. *NMFIS* represents the negative model-free implied skewness. *SlopeD* measures the steepness of the function that relates implied volatility to moneyness. *WFR* is the workforce uncertainty in the headquarters county. 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 control variables from Table 3 and 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)
WFR	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	0.536	0.567
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)
WFR	0.0022***	0.0018***	0.0022***	0.0018***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Controls	Yes	Yes	Yes	Yes
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

Table 5. The effect of PDMPs implementation on firm option-implied downside risk: Propensity score matching (PSM) approach

This table presents the impact of staggered PDMPs implementation on firm downside risk 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*, *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. *WFR* is the county-level workforce uncertainty. *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 risk. In column (1), we first include county-level variables from Table 3, and county and year fixed effects. In columns (2) and (3), we include all control variables from Table 3 and firm and year fixed effects in the regressions. Standard errors are clustered at the state level and are reported in parentheses. In Panel B, we compare matched variables between the treatment and control firms. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: The effect of PDMPs on firm downside risk

	County-level analysis	Firm-level analysis	
Dependent variable	WFR (1)	NMFIS (2)	SlopeD (3)
Treat×Post	−1.9656**	−0.0327**	−0.0421***
	(0.9676)	(0.0149)	(0.0118)
Post	—	0.0034	0.0123
		(0.0112)	(0.0115)
Controls	Yes	Yes	Yes
Firm FE	No	Yes	Yes
County FE	Yes	No	No
Year FE	Yes	Yes	Yes
Observations	6,365	15,005	15,005
adj-R^2	0.761	0.556	0.544

Panel B: Comparison between treatment firms and control firms

Match variable	Treatment group (1)	Control group (2)	Difference (3)	p-value (4)
Log(Assets)	6.9040	6.8364	0.0676	0.3180
Dividends/net income	0.1631	0.1608	0.0023	0.9120
Debt/assets	0.2015	0.2004	0.0011	0.8960
EBIT/assets	0.0547	0.0584	−0.0037	0.5810
CapEx/assets	0.0520	0.0500	0.0020	0.4060
Book-to-market	0.5224	0.5280	−0.0056	0.6890
Returns	0.0771	0.0691	0.0080	0.7670

Table 6. Alternative measure: Firm-level workforce uncertainty calculated from establishment counties

This table presents the regression results of workforce uncertainty on downside risk using an alternative measure of firm exposure to the workforce risk. 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. WFR_{Mean} is the average workforce uncertainty of all establishments for each firm each year. WFR_{EW} is computed by weighting each establishment's county workforce uncertainty by its number of employees, then averaging across all of a firm's establishments. Control variables include firm-level variables from Table 3 and county-level variables aggregated from the counties of the establishments, all of which 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 panel regression results using the two alternative measures of firm exposure to the workforce risk. 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
WFR_{Mean}	21,998	15.018	6.606	10.327	13.246	18.768
WFR_{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)
WFR_{Mean}	0.0035*** (0.0012)	0.0025** (0.0012)	—	—
WFR_{EW}	—	—	0.0023*** (0.0011)	0.0022** (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 7. The effect of PDMPs implementation on firm option-implied downside risk: Aggregating shocks from firm establishments

This table presents alternative measures for the PDMPs implementation on downside risk, 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. $PDMP_{Mean}$ equals one if more than 80% of a firm's establishments are located in counties that implemented 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 that implemented PDMPs in a given year, and zero otherwise. We include control variables from Table 3 and 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 8. Cross-sectional tests on the role of labor intensity

This table presents the effect of workforce uncertainty on firm downside risk 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. *WFR* is the workforce uncertainty 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 control variables from Table 3 and 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)
WFR	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 (High−Low)	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 workforce uncertainty on firm downside risk conditional on the labor supply of the firms' headquarters county. *NMFIS* is the negative model-free implied skewness. *SlopeD* is the steepness of the function that relates implied volatility to moneyness. *WFR* is the workforce uncertainty 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 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 control variables from Table 3 and 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)
WFR	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. Cross-sectional tests on the role of investor attention to labor issues

This table presents the effect of workforce uncertainty on firm downside risk conditional on investor attention to labor issues. *NMFIS* is the negative model-free implied skewness. *SlopeD* is the steepness of the function that relates implied volatility to moneyness. *WFR* is the workforce uncertainty in the headquarters county. Investor attention is proxied by Google search volume at the state-year level. For each year, we divide all states in our sample into two groups according to the median level of investor attention. Firms headquartered in states with investor attention above the median are categorized as "High Attention," while other firms are categorized as "Low Attention." We re-run our baseline panel regressions for the two sub-groups, respectively. We include control variables from Table 3 and 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 Attention (1)	Low Attention (2)	High Attention (3)	Low Attention (4)
WFR	0.0040***	0.0008	0.0024***	0.0014*
	(0.0012)	(0.0008)	(0.0009)	(0.0008)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	12,793	16,317	12,793	16,317
adj-R^2	0.549	0.578	0.559	0.576
Difference (High−Low)	0.0032***		0.0010***	
p-value	(0.0000)		(0.0000)	

Table 11. Cross-sectional tests on the role of hedging activities

This table presents the effect of workforce uncertainty on firm downside risk conditional on firms' hedging activities. *NMFIS* is the negative model-free implied skewness. *SlopeD* is the steepness of the function that relates implied volatility to moneyness. *WFR* is the workforce uncertainty in the headquarters county. For each year, we classify our sample firms into two groups based on whether they have hedge gains/losses according to income statement data from Compustat. Firms with hedge gains/losses are labeled as "Hedger" firms, and other firms are labeled as "Non-hedger" firms. We re-run our baseline panel regressions for the two sub-groups, respectively. We include control variables from Table 3 and 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	
	Non-hedger	Hedger	Non-hedger	Hedger
	(1)	(2)	(3)	(4)
WFR	0.0024***	0.0002	0.0015**	0.0007
	(0.0007)	(0.0016)	(0.0007)	(0.0014)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	31,234	4,613	31,234	4,613
adj-R^2	0.545	0.667	0.564	0.658
Difference (Non−Hedger)	0.0022***		0.0008***	
p-value	(0.0000)		(0.0000)	

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
WFR	WFR represents a firm's workforce uncertainty, measured by the opioid death rate in the headquarters' county. This rate is calculated as the number of opioid-related deaths per 100,000 residents, adjusted for the county's population.	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($\text{Population}_{\text{Mean}}$)	Log($\text{Population}_{\text{Mean}}$) is the log of the average population of all establishments for each firm each year.	Bureau of Economic Analysis (BEA), YTS
Log($\text{Per capita income}_{\text{Mean}}$)	Log($\text{Per capita income}_{\text{Mean}}$) is the log of the average per capita income of all establishments for each firm each year.	Bureau of Economic Analysis (BEA), YTS
$\text{Population growth}_{\text{Mean}}$	$\text{Population growth}_{\text{Mean}}$ is the average population growth of all establishments for each firm each year.	Bureau of Economic Analysis (BEA), YTS
$\text{Employment growth}_{\text{Mean}}$	$\text{Employment growth}_{\text{Mean}}$ is the average employment growth of all establishments for each firm each year.	Bureau of Labor Statistics (BLS), YTS
Log($\text{Population}_{\text{EW}}$)	Log($\text{Population}_{\text{EW}}$) 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($\text{Per capita income}_{\text{EW}}$)	Log($\text{Per capita income}_{\text{EW}}$) 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
$\text{Population growth}_{\text{EW}}$	$\text{Population growth}_{\text{EW}}$ 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
$\text{Employment growth}_{\text{EW}}$	$\text{Employment growth}_{\text{EW}}$ 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)
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 number of jobs posted by a firm within the year t+1 divided by the number of employees in year t, and then adjust this measure at the industry level.	Compustat, RavenPack Job Analytics

Other variables		
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, and then adjust this measure at the industry level.	Compustat, RavenPack Job Analytics
Non-computer job posting ratio	Non-computer job posting ratio is the number of non-computer occupation jobs posted by a firm within the year t+1 divided by the number of employees in year t, and then adjust this measure at the industry level.	Compustat, RavenPack Job Analytics
Computer job posting ratio	Computer job posting ratio is the 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, and then adjust this measure at the industry level.	Compustat, RavenPack Job Analytics
WFR_{Mean}	WFR_{Mean} is the average workforce uncertainty of all establishments for each firm each year.	CDC, YTS
WFR_{EW}	WFR_{EW} is computed by weighting each establishment's county workforce uncertainty by its number of employees, then averaging across all of a firm's establishments.	CDC, YTS
WFR_{Raw}	WFR_{Raw} is the workforce uncertainty proxied by the opioid-related death rate directly obtained from the CDC WONDER database.	CDC
$\text{WFR}_{\text{Narrow}}$	$\text{WFR}_{\text{Narrow}}$ is the workforce uncertainty proxied by the opioid-related death rate that restricts multiple causes to natural and semisynthetic opioids, other synthetic opioids, and heroin.	CDC
$\text{WFR}_{\text{Adults}}$	$\text{WFR}_{\text{Adults}}$ is the workforce uncertainty proxied by the opioid-related death rate that restricts people to working-aged adults (aged 25–64 years).	CDC
$\text{WFR}_{\text{Robust}}$	$\text{WFR}_{\text{Robust}}$ is the workforce uncertainty proxied by 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
$\text{WFR}_{\text{Heart}}$	$\text{WFR}_{\text{Heart}}$ is the death rate from the leading cause of death (per 100,000 people), which is heart disease.	CDC
WFR_{Top3}	WFR_{Top3} is the death rate from the top three causes of death (per 100,000 people), which are heart disease, cancer, and accidents.	CDC
$\text{WFR}_{\text{Alcohol}}$	$\text{WFR}_{\text{Alcohol}}$ is the percentage of interviewees identified as heavy drinkers in a state.	CDC
WFR_{All}	WFR_{All} is the death rate of all the causes (per 100,000 people) in the headquarters county.	CDC
Sales growth	Sales growth is the annual growth rate of sales for each firm.	CRSP, Compustat
Employee growth	Employee growth is the annual growth rate in the number of employees for each firm.	CRSP, Compustat
Log(1+patent)	Log(1+patent) is the logarithm of one plus the number of patents held by each firm annually.	KPSS, USPTO

Other variables		
Log(1+citation)	Log(1+citation) is the logarithm of one plus the truncation-adjusted patent citations for each firm annually.	KPSS, USPTO
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	PDMP equals one after PDMPs are effective in a county, and zero otherwise.	Prescription Drug Abuse Policy System
$\text{PDMP}_{\text{Mean}}$	$\text{PDMP}_{\text{Mean}}$ 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
PDMP_{EW}	PDMP_{EW} 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
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)
Investor attention	Investor attention is proxied by Google search volume at the state–year level, which is the average of the Google search volume index for the specific terms "workforce" and "labor."	Google Trends

Appendix B

Table B1. Robustness and placebo tests

Panel A of this table presents panel regression results of workforce uncertainty on downside risk focusing 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 restricted to counties with populations exceeding 1,000,000. *NMFIS* is the negative model-free implied skewness. *SlopeD* measures the steepness of the function that relates implied volatility to moneyness. *WFR* is the workforce uncertainty in the headquarters county. Panel B shows firm-level regressions of downside risk on placebo mortality measures. WFR_{Heart} is the death rate from the leading cause of death (per 100,000 people), which is heart disease. WFR_{Top3} is the death rate from the top three causes of death (per 100,000 people), which are heart disease, cancer, and accidents. WFR_{All} is the death rate of all causes (per 100,000 people) in the headquarters county. Panel C excludes firms in the healthcare (SIC codes 8011–8099) and pharmaceutical industries (SIC codes 2830–2839) from the main sample. We include control variables from Table 3 and firm and year fixed effects in all 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: Large counties				
Dependent variable	County population > 500k		County population > 1 million	
	NMFIS	SlopeD	NMFIS	SlopeD
	(1)	(2)	(3)	(4)
WFR	0.0028***	0.0022***	0.0032***	0.0032***
	(0.0008)	(0.0007)	(0.0010)	(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 B: Placebo test						
Dependent variable	NMFIS	SlopeD	NMFIS	SlopeD	NMFIS	SlopeD
	(1)	(2)	(3)	(4)	(5)	(6)
WFR_{Heart}	−0.0001	−0.0001	—	—	—	—
	(0.0002)	(0.0001)				
WFR_{Top3}	—	—	−0.0000	−0.0000	—	—
			(0.0001)	(0.0001)		
WFR_{All}	—	—	—	—	−0.0000	−0.0000
					(0.0001)	(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

Panel C: Excluding healthcare and pharmaceutical firms				
Dependent variable	NMFIS	SlopeD	NMFIS	SlopeD
	(1)	(2)	(3)	(4)
WFR	0.0026***	0.0020***	0.0026***	0.0020***
	(0.0007)	(0.0006)	(0.0007)	(0.0007)
Controls	Yes	Yes	Yes	Yes
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 B2. The effect of PDMPs implementation intensity on firm option-implied downside risk: Propensity score matching (PSM) approach

This table presents the impact of staggered PDMPs implementation intensity on firm downside risks using a propensity score matching (PSM) approach. Panel A describes the nine policy features used to construct the PDMP intensity measure. Each feature is coded based on the PDAPS database following collapsed response categories that reflect increasing levels of monitoring and access. The PDMP intensity score (*PDMPscore*) is computed as the average of the nine feature scores at the state-year level. Panel B reports the impact of PDMPs implementation intensity on firm downside risk. 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*, *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. *Post* is a dummy variable equal to one for the years after PDMPs implementation, and zero otherwise. We include all control variables from Table 3 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: Components of the PDMP intensity measure		
No.	PDMP Feature	Description of PDMP intensity measure
1	Reporting to law enforcement	Indicator for whether reporting to law enforcement is required or permitted (0 = No, 1 = Yes).
2	Reporting to professional licensing bodies	Indicator for whether reporting to professional licensing bodies is required or permitted (0 = No, 1 = Yes).
3	Reporting to prescribers or dispensers	Indicator for whether reporting to prescribers or dispensers is required or permitted (0 = No, 1 = Yes).
4	Drug schedules reported to PDMP	Degree of drug schedule coverage (0 = No reporting; 1 = Federal schedules II–V; 2 = All federal schedules II–V).
5	Reporting frequency	Frequency with which dispensers must report data to the PDMP (0 = No reporting; 1 = Reporting every 8 days or longer / unspecified; 2 = Reporting at least weekly).
6	Law enforcement access to PDMP data	Conditions under which state law enforcement can access PDMP data (0 = No access; 1 = Access with subpoena, warrant, or active investigation; 2 = Access with no restrictions).
7	Prescriber access to PDMP data	Access to PDMP data by healthcare providers (0 = No access; 1 = Patient and prescriber access).
8	Interstate data sharing	Whether the PDMP can share data with other state PDMPs (0 = No, 1 = Yes).
9	Mandatory PDMP check	Whether prescribers are required to check the PDMP when prescribing controlled substances (0 = No, 1 = Yes).

Panel B: The impact of PDMP intensity on downside risk		
Dependent variable	NMFIS (1)	SlopeD (2)
PDMPscore×Post	-0.0506^{**}	-0.0462^{***}
	(0.0202)	(0.0143)
Post	0.0047	0.0068
	(0.0124)	(0.0100)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	15,005	15,005
adj-R^2	0.558	0.542

Table B3. The effect of PDMPs implementation on firm option-implied downside risk: Alternative identification methods

This table presents the impact of PDMP implementation on firm downside risk using alternative methods. *NMFIS* is the negative model-free implied skewness. *SlopeD* is the steepness of the function that relates implied volatility to moneyness. *WFR* is the workforce uncertainty in the headquarters county. *PDMP* equals one after PDMPs are effective in a headquarters county, and zero otherwise. Panel A uses a staggered difference-in-differences (DID) analysis on the whole sample. Firms relocated to another state are further excluded, and control variables in Table 3 are included. We include firm and year fixed effects. Standard errors are clustered at the state level and are reported in parentheses. Panel B uses a stacked DID method. We examine a five-year window around the PDMPs implementation, and exclude firms with headquarters relocation. We include control variables from Table 3 and firm-cohort and year-cohort fixed effects. Standard errors are clustered at the county-cohort level and are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Staggered DID method		
Dependent variable	NMFIS (1)	SlopeD (2)
PDMP	−0.0385**	−0.0301***
	(0.0155)	(0.0116)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	31,479	31,479
adj-R^2	0.549	0.565

Panel B: Stacked DID method		
Dependent variable	NMFIS (1)	SlopeD (2)
PDMP	−0.0353***	−0.0344***
	(0.0099)	(0.0087)
Controls	Yes	Yes
Firm-cohort FE	Yes	Yes
Year-cohort FE	Yes	Yes
Observations	35,308	35,308
adj-R^2	0.560	0.565

Table B4. The effect of PDMPs implementation on firm option-implied downside risk: 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. *WFR* is the workforce uncertainty in the headquarters county. *PDMP* equals one after PDMPs are effective in a headquarters county, and zero otherwise. We include control variables from Table 3 and 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.

Dependent variable	First stage	Second stage	
	WFR	NMFIS	SlopeD
	(1)	(2)	(3)
PDMP	−2.0664***	—	—
	(0.5814)		
WFR	—	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
adj-R^2	0.788	0.548	0.564
F-statistic	12.63	—	—
p-value	(0.0004)	—	—
Cragg-Donald-Wald F-statistic	435.07	—	—

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

This table presents the effect of workforce uncertainty on firm downside risk 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. *WFR* is the workforce uncertainty 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. 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 are categorized as "High Male Proportion," while firms below the median are categorized as "Low Male Proportion." We re-run our baseline panel regressions for the two sub-groups, respectively. We include control variables from Table 3 and 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)
WFR	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)	