

# Newspaper Closures and Trading in Local Stocks

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## ABSTRACT

There is increasing awareness of how local media affects financial markets, but also of the endogeneity of media coverage. We separate the causal impact of local media on financial markets from selection effects using a new, hand-collected database of newspaper closures. We find that at least 29% of local newspaper closures are driven by distress, and thus, likely endogenous to local economic conditions. Return volatility and idiosyncratic risk decrease significantly after non-distress-driven newspaper closures, but increase after distress-driven closures, suggesting the presence of substantial selection effects. We find similar patterns for liquidity and trading. Once we account for selection, the estimated impact of local newspapers on volatility increases by over 40%. The reduction in volatility after non-distress-driven newspaper closures is larger for stocks subject to greater information frictions, lower national media coverage, firms located in remote areas, firms with a more concentrated geographic presence, and during recessions. All these tests suggest that investor information processing is the main channel that drives our results. Our findings highlight that the effect of media on financial markets may be larger than previously documented.

*JEL Classification:* G14, G33, L82

*Keywords:* media coverage, information processing, financial markets, return volatility, trading

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Local newspapers have been vanishing at an accelerating pace in the United States. In 2022, one in five Americans live in a “news desert”, a county with one or no local newspaper. Local newspaper circulation fell 40% from 2015 to 2020, while the number of newsroom employees dropped by 51% between 2008 and 2019, followed by an even larger decline due to the economic impact of COVID-19 ([Pew Research Center, 2022](#)). Local newspapers often close due to tough economic conditions ([Abernathy, 2022](#)) and re-establishing local media outlets is more difficult in economically disadvantaged areas ([Malone, 2022](#)).

Research on geography and finance has shown that investors overweight local stocks in their portfolios ([Coval and Moskowitz, 1999](#), [Ivković and Weisbenner, 2005](#)), and pay more attention to local stocks ([Cziraki, Mondria, and Wu, 2021](#)). Consequently, local investors may rely heavily on local media sources for their investment decisions, as these sources are more likely to contain high-quality investigative journalism ([Abernathy, 2022](#)).

Connecting the above insights, this paper studies the effect of local media closures on financial markets—a treatment effect—, taking into account that such closures are often driven by distress—a selection effect. We collect detailed data on newspaper closures and conduct a narrative classification of the reason for each closure, allowing us to make progress on separating these two effects.

First, we assemble a new sample of newspaper closures for the period 2001-2021. The U.S. News Deserts Project reports that newspapers were closed at an increasing rate during this period. A key advantage of our new dataset is that we register closure dates at monthly frequencies, unlike the vast and widely used database assembled by [Gentzkow, Shapiro, and Sinkinson \(2011\)](#)—as their underlying source, the Editor and Publisher Yearbook, is published every four years.

Second, we study the *circumstances* of newspaper closures and use a narrative analysis to

identify those that are more likely distress-driven (a closure following a drop in circulation or declining revenues) from those that occur for other reasons (the death of the founder or the consolidation of newspapers within the same media group). Examining the reasons for newspaper closures helps with the identification of causal effects. For example, local economic decline and cultural factors such as corruption (see, e.g. [Parsons, Sulaeman, and Titman, 2018a,b](#)) can lead to newspaper closures and to various firm-level outcomes such as fraud or investor demand.

We find that at least 29% of closures are due to financial or economic distress. For brevity, we refer to such closures as ‘distress-driven’ throughout the paper. We classify a closure as distress-driven if financial or economic distress is mentioned as a reason for the newspaper’s closure in any of our data sources. There are two benefits to this approach. First, its simplicity guarantees transparency and ease of replication—including extension to other settings. Second, it is conservative and will underestimate the number of newspapers closed for reasons endogenous to local conditions. The remaining 71% of observations will thus consist of newspaper closures that are truly not distress-driven, as well as closures that are distress-driven but were not reported as such. For brevity, we refer to such events as ‘non-distress-driven’ closures. As a validity check, we show that local stock returns decrease significantly in the year before distress-driven closures, but not before non-distress-driven closures.

We next show that separating distress-driven and non-distress-driven newspaper closures leads to markedly different effects for proxies of individual investor trading and information processing. Return volatility moves in the opposite direction after distress-driven vs. non-distress-driven newspaper closures. Using a stacked differences-in-differences model, we show that stock return volatility and idiosyncratic risk decrease significantly after non-distress-

driven closures but increase significantly after distress-driven closures of newspapers in the same ZIP code as the firm’s headquarters. These differences are economically significant. Idiosyncratic volatility declines by 1.3 percentage points, or 4% of one standard deviation, after non-distress-driven closures. However, it *increases* by 1.1 percentage points, or 3% of one standard deviation, after distress-driven closures.

Our results are robust to saturating the model with more granular, state  $\times$  year, fixed effects, or to using a narrower time period around newspaper closures. Further, firms affected by distress-driven and non-distress-driven closures differ not only with respect to pre-closure stock returns, but also with respect to observable firm characteristics. To account for this, we separately select control firms for each of these two sets. When using matched control firms, we confirm the decrease in return volatility and idiosyncratic risk for non-distress closures at comparable economic magnitudes relative to the results without matching. We also find similar results if we account for firms’ presence in multiple states ([Garcia and Norli, 2012](#)). Last, our results are not driven by changes in firm profitability or asset risk.

Looking at other proxies of investor trading, we find that non-distress-driven closures are followed by statistically significant reductions in trading volume and liquidity. Share turnover declines by 6.8 percent, [Amihud \(2002\)](#) illiquidity increases by 0.45, which represents 5% of one standard deviation, and the proportion of zero-return days ([Lesmond, Ogden, and Trzcinka \(1999\)](#)) increases by one percentage point, or 3% of one standard deviation, suggesting that investors trade less following non-distress-driven newspaper closures. None of these changes are present for distress-driven newspaper closures, and, similarly to the volatility results, the point estimate has the opposite sign for these outcomes.

Further, we document that the decrease in information processing is accompanied by decreases in other measures of investor attention. The number of tweets, and EDGAR

visits about the firm decrease significantly after non-distress-driven closures, and with a much smaller economic magnitude after distress-driven closures. Attention measured by StockTwits messages increases after distress-driven, yet decreases after non-distress-driven closures. Hence, when a local newspaper shuts down, it is not obvious that other information outlets take its place to substitute for the loss. Last, we find that firms expand their investor relation-specific website contents after non-distress-driven closures, but not after distress-driven closures. These differences reinforce that it is important to separate distress-driven newspaper closures from other closures.

If the above changes reflect the reduction in local investors' access to information, they should be larger in settings where information about local firms is more valuable. Consistent with this prediction, we find that the reduction in volatility following non-distress-driven newspaper closures is greater for stocks that are subject to larger information frictions. The drop in volatility doubles for small firms and growth firms, stocks of firms located in sparsely-populated areas of the U.S., firms operating in few locations (thus better fitting the definition of 'local'), and more than doubles during recessions. We also find a larger drop in volatility for firms with lower previous media coverage and Google search volume. These findings support our interpretation that newspapers contain relevant information about local firms, and that the loss of this information matters for local investors.

Taken together, these results allow us to separate the causal effect of local newspaper closures from the selection effect of which local newspapers are closed. The selection effect is positive, consistent with the intuition of [Garcia \(2013\)](#) and [Roth, Settele, and Wohlfart \(2022\)](#): investors in areas with economic distress have greater incentives to process information about local firms because of personal exposure and uncertainty. However, accounting for this selection effect, the treatment effect of newspaper closures on volatility is negative

and significant. We estimate the selection effect for distress-driven closures at 2.4 percentage points in terms of idiosyncratic volatility, which corresponds to 7% of one standard deviation. As an alternative way to show the value of our narrative classification, we pool distress-driven and non-distress-driven newspaper closures, as if we (the researcher) had no further information on these events, and re-estimate the same differences-in-differences model. Under this hypothetical, we find a 41-43% attenuation of the estimated treatment effect, suggesting that the selection effect is quantitatively important.<sup>1</sup>

Our work contributes to three strands of the academic literature. First, our results advance the literature on the role of the media in financial markets (Fang and Peress, 2009, Dougal, Engelberg, Garcia, and Parsons, 2012), focusing on local newspapers. Gao, Lee, and Murphy (2020) use the original Gentzkow et al. (2011) data to study municipal bond yields and Heese, Pérez-Cavazos, and Peter (2021) use an additional 33 newspaper closures to examine corporate fraud.<sup>2</sup> We hand-collect all newspaper closures for 2001-2021 and classify them based on the reason for the closure. Our more recent and detailed data allows for a nuanced analysis of the underlying mechanisms.<sup>3</sup> We document that many local newspaper closures—almost one in three—are distress-driven, and, consequently, endogenous to economic conditions. Building on this insight, we separate selection and treatment effects and study how closures affect trading in local stocks.

Second, we contribute to the literature on the endogeneity of media coverage (Gurun

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<sup>1</sup>As section 3 explains, this estimate is a lower bound on the selection effect assuming perfectly accurate classification of distress-driven and non-distress-driven newspaper closures. If we mistakenly classified some newspaper closures as non-distress-driven, even though in reality they were distress driven, our estimate would understate the true selection effect.

<sup>2</sup>Kyung and Nam (2023) show that local newspaper closures are associated with higher returns to insider trading, while Allee, Cating, and Rawson (2025) show an association between total newspaper employment and proxies of local firms’ information environment in metropolitan areas.

<sup>3</sup>A further benefit of studying stocks is that individual investors are substantially more likely to own stocks than municipal bonds: 61% of Americans report owning stocks (Gallup, 2023), but only 2.4% own government bonds (Olson and Wessel, 2016, Bagley, Vieira, and Hamlin, 2022).

and Butler, 2012, Garcia, 2018, Goldman, Martel, and Schneemeier, 2022). Recognizing this endogeneity, previous studies have used a variety of empirical approaches to infer the causal effect of the media on financial outcomes (Engelberg and Parsons, 2011, Peress, 2014). We provide evidence on the reasons for newspaper closures, and use this variation to estimate the selection effect of endogenous media coverage. By doing so, we address the point raised in Tetlock (2014) that large-scale empirical studies of the media on financial markets report much smaller effects compared to anecdotal studies focusing on the publication of single articles.<sup>4</sup> Our findings on the attenuating effect of selection helps reconcile these two facts.

Finally, our work also adds to the literature on the informational advantage of local investors (Coval and Moskowitz, 2001, Chhaochharia, Kumar, and Niessen-Ruenzi, 2012) and their propensity to pay more attention to local information (Cziraki et al., 2021, Mengoli, Pagano, and Pattitoni, 2024). We contribute to this literature by characterizing the importance of local newspapers in local investors’ information processing.<sup>5</sup>

## 1 Background and predictions

We summarize predictions for our empirical analysis based on previous theoretical and empirical work.<sup>6</sup>

The first set of predictions concerns local investor information processing as information supplied by the media changes—in our setting: a local newspaper closes. Theoretical work

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<sup>4</sup>“First, anecdotal studies suggest the impact of media on asset prices could be enormous, with the publication of single articles causing prices to rise or fall by factors of three to six. But the large-scale evidence from studies using instruments for exogenous changes in media reporting reveals impacts that are smaller by an order of magnitude. One can reconcile these facts by arguing either the anecdotes are unusual or the instruments are weak.” (Tetlock, 2014, p.380.)

<sup>5</sup>More broadly, our results also relate to the literature on the reasons for investor disagreement (Cookson and Niessner, 2020, Huang, Hwang, Lou, and Yin, 2020), highlighting the role of differential exposure to local media sources.

<sup>6</sup>See Tetlock (2014) for a review about information transmission in financial markets.

predicts that a higher information content of news increases trading activity (Tetlock, 2010), and that media coverage increases stock price informativeness (Goldman et al., 2022). Mondria (2010) and Van Nieuwerburgh and Veldkamp (2009, 2010), show that local investors' information processing and trading decisions endogenously amplify each other. Based on this work, we expect a negative treatment effect: local newspaper closures should reduce information processing, and thus trading, by local investors.

The second set of predictions is aimed at understanding a potential selection effect: Newspaper closures can be endogenous to local economic conditions, which in turn also directly influence incentives to process information. Put differently, how does investor information processing change in areas where local newspapers tend to close?

In our setting, we ask whether investors tend to process more or less information about firms in distress, or in areas with a decaying local economy. Allocating different levels of attention to thriving vs. struggling firms is consistent with the model of Peng and Xiong (2006), which shows that limited investor attention leads to category learning. Empirical results on investor processing in good and bad times, or about good and bad firms, are mixed. On the one hand, using time-series variation in the state of the overall economy, Garcia (2013) finds that financial newspaper articles predict stock returns only during recessions. The incentives to process information increase with personal exposure and uncertainty (Roth et al., 2022), which is particularly high during bad times. On the other hand, there is theoretical and empirical evidence that demand for information is greater during booms. Van Nieuwerburgh and Veldkamp (2006) develop a model of asymmetric learning, where greater levels of production lead to more precise information during booms. Studies focusing on firm performance show that individual investors process more information before buying a stock

than before making sell decisions (Barber and Odean, 2008, Hartzmark, 2015).<sup>7</sup> Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) study an attention allocation model in which information production also varies with the business cycle: investors process information about the aggregate shocks in recessions, while processing information about idiosyncratic shocks in booms, leading to price informativeness varying procyclically as well. In sum, existing theoretical and empirical results yield ambiguous predictions about the sign of the selection effect in our setting.

## 2 Data on newspaper closures and affected firms

### 2.1 Data sources on newspaper closures and firm financials

We hand-collect information on newspaper closures identifying the month of each closure. Doing so allows us to link the data to financial market outcomes more precisely relative to the database of Gentzkow et al. who rely on a yearbook published every four years. Our sample covers closures between 2001 and 2021, extending Gentzkow et al.’s database by 16 years. We start with the list of discontinued newspapers published in English in the “Chronicling America” project, which is part of the National Digital Newspaper Program, while we restrict attention to the years 2001 to 2021. We complement this list with the U.S. News Desert Project database<sup>8</sup>, which yields 637 potential closures since 2001. For each of these newspapers, we conduct additional manual searches using Factiva, WorldCat.org, the respective newspapers themselves, regional newspaper archives and libraries, local websites, and blogs (accessed through general online search engines), to validate that the newspaper

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<sup>7</sup>In contrast to these findings on individual investors Bowles and Reed (2023) find that *mutual funds* process more information about firms whose stocks they short than firms whose stocks they are long.

<sup>8</sup>We thank Penelope Muse Abernathy for kindly sharing the U.S. News Deserts database with us.

has discontinued, to identify the precise date of the last publication, and to collect additional information about the reasons and circumstances behind the closure. We restrict attention to validated newspapers for which we can identify the closure date and which can be merged to ZIP codes with publicly-traded firms, resulting in a sample of 263 newspaper closures.

We consider a firm to be affected by the newspaper closure if it is headquartered in the same ZIP code that the newspaper operated in.<sup>9</sup> We merge these data with information on stock prices from CRSP and accounting data from Compustat. We drop a newspaper closure if there are no publicly-traded firms with Compustat and CRSP data in the ZIP code. Panel A of Table 1 shows the number of newspapers closed each year for which there is at least one affected firm. Newspapers close more frequently starting in 2006. The year 2010 shows the highest number of closures.<sup>10</sup>

Table 1 Panel A also shows the number of firms affected by newspaper closures over time. Overall, 3,717 firms were affected by a closure over the sample period: 1,096 by distress-driven closures and 2,621 by non-distress-driven closures. The year 2010 has the largest number of affected firms with 513, representing approximately 14% of all affected firms.

Panel B of Table 1 shows descriptive statistics of firm and stock characteristics of affected firms and never-affected firms at time  $t - 1$  prior to the closure event at time  $t$ . Affected firms tend to be substantially larger both in terms of total assets (USD 5.1 billion versus USD 2.8 billion) and market capitalization (USD 3.7 billion versus USD 1.9 billion). Tobin's Q of affected firms with an average of 2.0 is also above the average of never-affected firms with 1.7. Affected firms tend to have slightly higher sales growth and report higher R&D expenditures. Despite these differences in firm characteristics, stock return distributions seem comparable,

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<sup>9</sup>This assumption likely leads us to underestimate the effect of newspaper closures, as many local newspapers circulate in more than one ZIP code and likely also cover local information in surrounding regions.

<sup>10</sup>While newspapers were closed also in 2002, these did not affect any firm by our definition of operating in the same ZIP code.

as return volatility, systematic risk and idiosyncratic risk are similar across both groups.<sup>11</sup>

Newspapers are more likely to cover local firms (Erdal, 2011, Gurun and Butler, 2012, Cagé, Hervé, and Viaud, 2020). To reinforce this claim for our sample period, we collect newspaper article contents from Factiva for a selection of S&P 500 firms and for 30 U.S. newspapers, 10 regional and 20 national. We count the number of articles that each newspaper publishes specifically about the firm in a given year. Using a panel consisting of triplets of newspaper-firm-year observations, we regress the number of articles about each firm on local firm-newspaper indicators and controls. The results in Internet Appendix Table A2 show that newspapers write significantly more articles covering firms in the same state, and in the same city. This result holds when we control for firm characteristics that could drive disclosure behavior (columns 1-2), and even when we capture firm-specific time-varying heterogeneity using firm  $\times$  year fixed effects (column 3).

## 2.2 Newspaper closure motives

### 2.2.1 Narrative classification of closure motives

To better understand the dynamics of local newspaper closures, we hand-collect information on the reason for the newspaper closure and use a narrative classification method to separate distress-driven and non-distress-driven closures. Ramey (2016) defines a narrative method as “constructing a series from historical documents to identify the reason and/or the quantities associated with a particular change in a variable”. Starting with the seminal work of Friedman and Schwartz (1963) such methods have been used to identify various policy

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<sup>11</sup>The level of idiosyncratic risk in our sample is comparable to typical levels found in the literature. Eg.g., Ferreira and Laux (2007) document idiosyncratic volatility (the variance) of 19.4% for the period between 1990 and 2001, which is similar to our squared standard deviation of residuals of 21.0% for affected firms and 23.6% for never-affected firms.

shocks—e.g., [Poterba \(1986\)](#), [Romer and Romer \(1989, 2004, 2010\)](#), [Ramey and Shapiro \(1998\)](#), [Ramey \(2011\)](#).

Seventy-six closures (29%) are distress driven. Of these, 28 are the result of a takeover by another newspaper or media holding, while 48 are closures that are not associated with a takeover. We classify newspaper closures as distress-driven if financial distress, or M&A related to distress is one of the stated reasons for the closure. [Gilson, Hotchkiss, and Osborn \(2016\)](#) show that distressed firms have been increasingly relying on M&As as opposed to stand-alone reorganization within the Chapter 11 resolution process during the early part of our sample, 2002-2011.

We classify all other newspaper closures as 'non-distress-driven'. The most common reasons within the set of non-distress-driven closures are consolidation of different products within one media group (56) and mergers that are seemingly not driven by financial distress (49). Personal reasons include the illness or death of (one of) the owner(s), or relocation because of family circumstances. Our classification shows that newspaper closures are often related to distress. Hence, our narrative classification of the reason for closures will help disentangle various mechanisms for any potential correlation between closures and stock market outcomes. Internet Appendix A9 provides examples and further details on our classification.

### **2.2.2 Validating our classification**

To validate our classification of local newspaper closures, we investigate pre-event trends prior to distress and non-distress-driven closures. For each ZIP code, we construct an index of local stock returns, using firms that are located within a 250-mile radius of, following [Seasholes and Zhu \(2010\)](#). We run a stacked difference-in-differences analysis, where we regress ZIP-level stock returns on event-time dummies around the closure year in  $t$ , while

we distinguish between distress and non-distress-driven closure events. Panel A of Figure 2 shows that local stock returns decline prior to a distress-driven newspaper closure. The event-time coefficients are slightly positive in  $t - 5$ , decrease slightly over the subsequent years, and turn negative in  $t - 1$ . In contrast, local returns prior to non-distress-driven newspaper closures fluctuate rather closely around zero and fail to be statistically significant at conventional levels.

There is substantial heterogeneity in terms of the number of publicly-traded firms located within a 250-mile radius around a newspaper closure, reflecting the diversity in economic density across the country. The number of firms ranges from 1 to 2,117 firms, with a mean of 623 and a median of 417. The differences in the number of firms introduce heterogeneity in the precision at which local returns are measured. In a robustness test we run the same analysis as before, while we restrict attention to ZIP codes for which we observe stock returns of at least 20 firms within a 250-mile radius. The results are shown in Panel B of Figure 2 and confirm the results before: prior to distress-driven closures, local stock returns decline, while there is no such pattern for non-distress-driven closures.

This analysis provides empirical support for the notion that distress-driven closures are correlated with regional economic trends, in contrast to non-distress-driven ones.

### 3 Empirical approach

How does the closure of a local newspaper affect return volatility, understanding that such closures are often economically motivated? To answer this question, we estimate a stacked difference-in-difference model with return volatility as the dependent variable, separating distress-driven from non-distress-driven newspaper closures. Due to well-known concerns

with the two-way fixed effects (TWFE) estimator when treatment is staggered in adoption and varies over time (De Chaisemartin and d’Haultfoeuille, 2020, Baker, Larcker, and Wang, 2022) we implement the estimator of Gormley and Matsa (2011) and Cengiz, Dube, Lindner, and Zipperer (2019), controlling for separate time and unit fixed effects for each event stack.

We build stacks consisting of firms affected by newspaper closures in the same ZIP code and those never affected by any such closure for each of the 20 event-years during our sample period. Each stack consists of firm-year observations during the event window spanning six years before to six years around the respective event year of both firms affected by a closure and the never-affected firms.

We estimate the following equation:

$$Y_{sit} = \beta_1 post_{sit}^D + \beta_2 post_{sit}^{ND} + \gamma X_{sit} + \nu_{si} + \mu_{st} + \varepsilon_{sit} \quad (1)$$

where  $i$  denotes the firm,  $t$  denotes the year,  $s$  denotes the stack defined by the event year,  $y$  is a risk measure,  $post^D$  is a dummy variable set to 1 for firms affected by a distress-driven closure in the same ZIP code after the closure, and to zero otherwise,  $post^{ND}$  is a dummy variable set to 1 for firms affected by a non-distress-driven closure in the same ZIP code after the closure and to zero otherwise,  $\nu_i$  are stack-specific firm fixed effects, and  $\mu_{st}$  are stack-specific year fixed effects.

If our classification method were perfect, all distress-driven closures would be truly distress-driven and all non-distress-driven closures would be truly not driven by distress. In this ideal case, we expect that the estimated coefficient for distress-driven closures will reflect both the selection effect (that local newspapers in certain areas and times are more likely to close) and the treatment effect (that a newspaper closure changes stock price risk). In contrast, the estimated coefficient for non-distress-driven closures will reflect only the

treatment effect. To the extent that our classification method is imperfect, we expect that *some* closures that we classify as ‘non-distress-driven’ are, at least in part, distress-driven. This could occur, for example, if the original sources outright missed a distress motive, or because the true ‘proximate’ reason for the closure was an indirect consequence of distress occurring much earlier. In this case, even the coefficient estimate for non-distress-driven closures will reflect a selection effect, but a smaller one than the coefficient estimate for distress-driven closures. It follows that we can approximate the selection effect as the difference between the coefficient estimate for distress-driven closures less the coefficient estimate for other closures. To the extent that our classification is imprecise, we will underestimate the true selection effect.

## 4 Newspaper closures and trading in local stocks

### 4.1 Newspaper closures and volatility

We estimate a stacked differences-in-differences model to study the effect of newspaper closures on the return volatility of local stocks. We use return volatility and idiosyncratic risk as our proxies for investor trading ([Foucault, Sraer, and Thesmar, 2011](#), [Griffin, Hirschey, and Kelly, 2011](#)). [Andrei and Hasler \(2015\)](#) show, both theoretically and empirically, that investor information processing increases return volatility. For completeness, we also look at systematic risk as another outcome variable. Return volatility is the annualized standard deviation of stock returns. We estimate idiosyncratic volatility as the annualized standard deviation of residuals of a regression of daily excess stock returns over one full year on the daily three Fama-French factors. We calculate systematic volatility as the square root of the difference between the variance of daily stock returns and the variance of daily residuals.

Return volatility moves in opposite directions following distress-driven and non-distress-driven local newspaper closures. Column 1 of Table 3 shows that return volatility increases following distress-driven closures, with the coefficient statistically significant at the 5% level. In contrast, volatility *decreases* significantly following non-distress-driven closures, with the coefficient significant at the 1% level. Column 2 reveals a similar pattern for idiosyncratic risk, but with an even sharper contrast between distress-driven and other closures. The increase in idiosyncratic volatility is significant at the 5% level. The changes in volatility are also economically significant. Looking at column 2, the increase after distress-driven closures is 1.4 percentage points corresponding to 5% of one standard deviation. The decrease in idiosyncratic volatility after non-distress-driven closures is 1.2 percentage points, or 4% of one standard deviation. Last, systematic risk increases slightly, though not statistically significant after distress-driven closures, while it decreases significantly after non-distress-driven closures (column 3) with a magnitude of 4% of one standard deviation.

These results underscore the importance of accounting for the reason behind a local newspaper closure when considering its effect on financial outcomes. Relying on our narrative classification, we can infer the sign and magnitude of the selection and treatment effects of the loss of a local media outlet on firm risk. Based on our estimates, there is a negative and significant treatment effect of a local newspaper closure on firm risk: stock returns become less volatile when there is less local news coverage. Examining the difference between the coefficients for distress-driven and other closures, we can infer a positive and significant selection effect. The positive sign is consistent with the intuition of [Garcia \(2013\)](#) and [Roth et al. \(2022\)](#): investors in areas with economic distress have greater incentives to process information about local firms because of personal exposure and uncertainty. The selection effect, estimated as the difference between the coefficients for distress-driven and non-distress-driven

closures is substantial. Based on the estimates in column 2, the selection effect is 2.6 percentage points, which corresponds to 8% of the standard deviation of idiosyncratic volatility. As discussed in section 3, this estimate is a lower bound on the selection effect assuming perfectly accurate classification of distress-driven and non-distress-driven newspaper closures. If we classified some distress-driven newspaper closures as non-distress-driven, this estimate would understate the true selection effect.<sup>12</sup>

Panel B of Table 3 shows that using all newspaper closures—without classifying them—obfuscates the relation between newspaper closures and risk. Estimating a stacked DiD method using all newspaper closures in our sample would lead us to find a smaller, and less statistically significant effect of local newspaper closures on firm risk. This model would conflate distress-driven and other closures, and hence the treatment and selection effects of local newspaper closures. The difference is quantitatively important: the coefficient estimates for total return volatility and idiosyncratic volatility equal are 41-43% smaller relative to those estimated for non-distress-driven closures in Panel A of Table 3. Hence, the selection effect leads to a 41-43% attenuation of the estimated treatment effect in the overall sample.

Last, recognizing that firms affected by a closure might differ from never-affected firms, we repeat our analysis using a matched sample of control firms. Panel A of Table 4 documents substantial differences in terms of observable characteristics between firms affected by distress-driven and non-distress-driven closures at  $t - 1$  before the closure. These differences imply that we require separate models of how observable firm characteristics affect the likelihood of being subject to a distress-driven vs. a non-distress-driven closure. Hence, we

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<sup>12</sup>Local newspapers that remain open may also cut costs, lay off journalists, and reduce the focus on local news in an effort to increase efficiency. First, if anything, this trend would lead our estimates to understate the true treatment effect of local newspaper closures, because even the control group receives less local information than before. Second, we find no evidence of different pre-trends for non-distress-driven newspaper closures in Figure 3.

separately conduct Mahalanobis matching for the two subsamples, using the natural logarithm of market capitalization, Tobin’s Q, sales growth, leverage, profitability, and R&D at time  $t - 1$  to identify a comparable firm that was not affected by any newspaper closure.

We then repeat our analysis using these matched samples as controls in Panel B of Table 4. The results remain similar for total return volatility and idiosyncratic risk: both decrease significantly after other closures but not distress-driven closures. Interestingly, in this matched sample, we find no significant change in systematic risk for either type of newspaper closure, and virtually no difference between the point estimates of the coefficients for distress-driven and non-distress-driven closures.

## 4.2 Newspaper closures and measures of trading activity and liquidity

As further evidence that trading in local stocks changes after local newspaper closures, Table 5 studies how measures of trading activity and liquidity change after local newspaper closures. Column 1 shows that stock turnover decreases significantly by 6.8 percent after non-distress-driven newspaper closures, but not after distress-driven closures. Column 2 documents that [Amihud \(2002\)](#) illiquidity increases by 0.45, or 5% of one standard deviation. Last, the results in column 3 show that the proportion of zero-return days, a proxy for days with no trading ([Lesmond et al. \(1999\)](#)) increases by 1 basis point, which represents 3% of one standard deviation.<sup>13</sup> For both of the latter measures, the point estimate of the coefficient for distress-driven closures has the opposite sign, similar to our results for return volatility. In sum, trading activity and liquidity decrease significantly after non-distress-driven closures,

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<sup>13</sup>Placing this estimate in the context of our sample: only 5% of observations affected by a closure have any zero-return days, and the sample average of the variable is 5 basis points (not shown in a table).

but not after distress-driven closures, displaying a similar pattern to return volatility.

### **4.3 Dynamics of volatility around distress-driven and other newspaper closures**

Building on the finding that volatility moves in different directions after distress-driven and other newspaper closures, we now examine the dynamics of volatility these events in more detail. Figure 3 shows event-study graphs with idiosyncratic volatility as the dependent variable. The top panel shows the dynamics of idiosyncratic volatility around distress-driven newspaper closures and the bottom panel around other newspaper closures.

The two graphs show markedly different patterns for distress-driven vs. other closures. There is a noticeable downward trend in volatility occurring before distress-driven newspaper closures. However, there is a less pronounced, and not statistically significant decrease in idiosyncratic volatility between the year before the closure ( $t = -1$ ) and two years after it ( $t = 2$ ). In contrast, there is no evidence of any pre-trend prior to other newspaper closures in the bottom graph in Figure 3. Idiosyncratic volatility starts to decrease in the year of the newspaper closure and, after a monotonic decline, becomes significantly lower two years after the closure relative to the year before it. This graphic comparison of stock return volatility around distress-driven vs. other closures substantiates the differences between the two events, supporting the notion that the former are likely driven by selection effects whereas the latter are not, or to a lesser degree.

## 4.4 Robustness

The effect of non-distress-driven newspaper closures on volatility is robust to alternative empirical specifications of the stacked differences-in-differences model. We show that the main results in Section 4.1 are robust to allowing for time-varying regional trends. Table 6 Panel A estimates the same model as Panel A of Table 3 but replaces  $\text{year} \times \text{stack}$  fixed effects (FE) with  $\text{state} \times \text{year} \times \text{stack}$  FE. We continue to find that return volatility and idiosyncratic risk decrease significantly following non-distress-driven closures, while they increase significantly after distress-driven closures, with two minor differences. First, the positive coefficient for distress-driven closures increases by almost 50% relative to the main specification—e.g., from 1.4 to 2.1 for idiosyncratic volatility, with a similar increase for total return volatility. Second, the standard errors become slightly larger for both return volatility and idiosyncratic risk.

Next, we restrict the time window of the estimates to three years before to three years after each newspaper closure to focus more closely on the potential impact of the closure. Panel B of Table 6 shows that our main results continue to hold. Moreover, both the statistical and the economic significance of the coefficient increases slightly for non-distress-driven newspaper closures. For the regression of idiosyncratic risk, the absolute value of the coefficient for non-distress-driven closures increases by 12% relative to the main model in Panel A of Table 3.

We confirm that our results are not driven by changes in firm fundamentals, notably, profitability or asset risk. Table A4 in the Internet Appendix finds no change in profitability, sales growth, Tobin’s Q, the standard deviation of return on assets or the standard deviation of sales (of the next five years) after non-distress-driven newspaper closures.<sup>14</sup>

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<sup>14</sup>We also find no significant changes in these measures after distress-driven newspaper closures.

We explore whether the above findings can be interpreted as a drop in information processing after non-distress closures, acknowledging that idiosyncratic volatility can serve both as a measure of information activities and as a measure of noise. [Dávila and Parlato \(2023\)](#) show theoretically that the relation between volatility and informativeness is driven by two channels— noise reduction and equilibrium learning—and can be both negative and positive. They develop the comovement score, a measure of the likelihood that an asset’s return volatility is positively correlated with price informativeness. We calculate their measure and sort firms according to their comovement score in Table A5 in the Internet Appendix.<sup>15</sup> First, columns 1-2 split the sample into firms with a low ( $< 0.5$ ) and a high ( $\geq 0.5$ ) comovement score. The decrease in idiosyncratic volatility is smaller for low comovement score firms, and larger for high comovement score firms. The economic magnitude of the coefficient estimate is nearly twice as large in column 2. Consistent with the empirical results of [Dávila and Parlato \(2023\)](#) most comovement score values fall between 0 and 1. Nevertheless, in columns 3 and 4 we show estimates for firms with an estimated comovement score of 0 (5,483 obs., or 1.5% of our sample) and 1 (28,702 obs., or 7.7% of our sample). In column 3, the coefficients on *Post distress closure* and *Post non-distress closure* have the opposite signs relative to our baseline results and are not statistically significant at conventional levels. Hence, the pattern disappears for firms where volatility shows a negative relation with informativeness. Column 4 shows that idiosyncratic volatility increases after distress closures and decreases after non-distress closures, while the economic magnitude is greater than in our baseline results in Table 3 Panel A. Hence, our results are more pronounced for firms with a positive relation between volatility and informativeness. Collectively, these additional tests support

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<sup>15</sup>We sort observations at the firm level rather than the firm-year level, as the metric is constructed over 40 consecutive quarters and their algorithm requires non-missing data for all 40 quarters. These features lead to high auto-correlation within for observations of the same firm and to the exclusion of many observations for smaller, younger and high-growth firms from the sample.

the interpretation of changes in idiosyncratic volatility as changes in information.

Last, we find similar results if we extend our analysis to measure location more precisely for firms operating across multiple U.S. states—see Table A6 in the Internet Appendix. We change the unit of analysis to the state-year level and use the data from [Garcia and Norli \(2012\)](#) on the geographic dispersion of firm’s operations for the period 1994-2008. We define a firm as treated if there is a newspaper closure in any of the U.S. states in which it operates. We continue to find that idiosyncratic volatility decreases significantly after non-distress-driven newspaper closures, but not after distress-driven newspaper closures.<sup>16</sup>

In sum, our main results remain robust—and, in some cases, become stronger—when we saturate the main model with more granular fixed effects, use a narrower time window around newspaper closures to capture their effect on volatility, or vary the definition of local firms.

## 4.5 Measuring attenuation in our framework

Our narrative classification allows us to measure the attenuation of the estimated effect of local newspaper closures on trading in local stocks. We measure attenuation as the difference between the coefficient of *Post non-distress-driven* and the coefficient of the variable *Post closure*—which pools both distress-driven and non-distress-driven newspaper closures—scaled by the coefficient of *Post non-distress-driven*. The coefficient of *Post closure* is a hypothetical estimate that an econometrician would observe if they had no further information on the reason for the local newspaper closures.

Table 7 summarizes the magnitude of this attenuation across our various specifications

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<sup>16</sup>As expected, we estimate a smaller increase relative to our main analysis that uses ZIP-level information. First, the state-level analysis assumes that all firms in a state are affected by any local newspaper closure in a state. For large U.S. states such as California or Texas, this assumption is very imprecise. Second, defining closures at the state level leaves only six never-treated states: DE, ME, NH, NJ, UT, and WY. Last, the [Garcia and Norli \(2012\)](#) data end in 2008, so location data are less precise for the second part of our sample.

for idiosyncratic volatility (Panel A) and for the different outcome variables we study (Panel B). Table 7 Panel A shows that attenuation towards zero is substantial not only in the baseline model shown in Table 3, but across all alternative specifications. Our estimate of attenuation for idiosyncratic volatility ranges from 32% to 62%. Table 7 Panel B confirms that attenuation towards zero is present not only for idiosyncratic volatility, but for all of the proxies of investor trading we use. We find an attenuation of 26% for Amihud illiquidity, 18% for the proportion of zero-return days, and 12% for stock turnover. The consistent pattern of attenuation across model specifications and outcome variables further highlights the value of our new data and method in quantifying selection effects when considering the impact of (local) media on financial markets.

## 5 Heterogeneity and mechanism

### 5.1 Heterogeneity across firms and locations

Which stocks are affected the most by local newspaper closures? If investors use local newspapers to learn about local stocks, then we expect the treatment effect of a newspaper closure on return volatility to be larger for stocks that face greater information frictions, and in areas where information processing costs are higher. Table 8 shows differences in the effect of local newspaper closures on idiosyncratic risk, splitting the sample at the median value by various proxies of information frictions. We focus our subsample analysis on non-distress-driven local newspaper closures, but control for distress-driven closures as well to maintain a specification consistent with our main analysis.

We find that the effect of non-distress-driven newspaper closures is larger for stocks that are subject to greater information frictions. Table 8 Column 1 shows that the reduction in

idiosyncratic risk is larger for smaller firms. The coefficient estimate of -2.37 is statistically significant at the 1% level and almost twice as large as our estimate for the overall sample (-1.23 in Table 3 column 2). The effect of other newspaper closures is also significantly larger at firms with higher sales volatility, shown in column 2. The coefficient estimate of -2.24 is significant at the 1% level and nearly doubles the estimate for the overall sample. This result suggests that information contained in local newspapers is particularly helpful in gauging the prospects of firms with riskier or more cyclical operations. We also see a larger reduction in idiosyncratic volatility following other newspaper closures at firms with a higher market valuation (column 3), suggesting that the information in local newspapers is particularly important for high-growth stocks.

The last three subsample splits in Table 8 capture investor familiarity with the stock. We use advertising expenses to proxy for firms selling products mostly to retail consumers vs. those selling mostly to other businesses. Column 4 shows that the effect of other newspaper closures is more pronounced for stocks of firms with greater advertising expenses. This pattern may reflect a demand effect: investors are more likely to gather and process information from the local newspaper about firms whose brands and services they are familiar with. It may also reflect a supply effect: local newspapers are more likely to contain stories about firms that retail consumers are familiar with. In both cases, the closure of a local newspaper would lead to a greater drop in the availability of information about such firms, as compared to firms whose primary customers are other businesses.

Next, we separate the sample into high and low media coverage based on the number of Dow Jones news items about the firm in the previous year. On the one hand, greater news coverage may substitute for the information contained in a local newspaper. On the other hand, investors may choose to invest less of their portfolio in firms that rarely receive any

media coverage, and, as a result, may update their views about the stock very little even with the arrival of new information. Table 8 column 5 shows that idiosyncratic risk declines after other closures both at stocks with low and high previous media coverage, but the effect is more statistically and economically significant for stocks with low media coverage. This finding hints at some degree of substitution between information from local newspapers and other news sources. We explore this hypothesis in more detail in section 6.2.

Last, Table 8 column 6 shows a similar pattern using Google search volume from [deHaan, Lawrence, and Litjens \(2025\)](#) instead of media coverage. Idiosyncratic volatility declines over seven times more for firms below-median Google Search volume than for firms with above-median Google search volume. On balance, the findings in Table 8 suggest that the reduction in idiosyncratic volatility is more pronounced at smaller, riskier, and less-known firms.

Next, we turn to differences based on geographical characteristics. We expect non-distress-driven newspaper closures to have a larger effect on idiosyncratic volatility in remote, sparsely populated areas, as firms in such areas suffer from greater information asymmetries ([Coval and Moskowitz \(1999, 2001\)](#), [Ivković and Weisbenner \(2005\)](#)). We use the same model specification as before, in Table 8 and split the sample of newspaper closures into those in vs. outside of metropolitan areas, as well as three different cutoff values for population density: 750, 1,000, and 2,000 people per square mile.<sup>17</sup>

Table 9 shows that volatility decreases after non-distress-driven newspaper closures are concentrated in rural and sparsely populated areas, consistent with our prediction based on information frictions. Column 1 shows that the reduction in idiosyncratic risk after other newspaper closures is highly statistically significant outside of metropolitan areas. To quantify the differences more precisely, columns 2-4 show that the reduction in volatility is

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<sup>17</sup>The average population density inside U.S. cities is 1,600 according to the U.S. Census Bureau.

largest for stocks in areas with population density lower than 750 people per square mile. The coefficient of -2.36%, the effect is almost double the effect in the overall sample. As we increase the threshold for population density (to 1,000 and 2,000 people per square mile), the decline becomes less pronounced, and shrinks to -2.28% and 1.60% respectively, in line with these thresholds identifying less sparsely populated areas. Across all models, the coefficient estimates for rural and sparsely populated areas are statistically significant at the 1% level. We conclude that the effect of non-distress-driven newspaper closures is higher for stocks subject to greater information frictions.

Last, Table 9 column 5 splits the sample by the number of U.S. states in which the firm has operations. We find that the coefficient on non-distress-driven closures is 2.5 times the size of the baseline value for firms that operate in four or fewer U.S. states, and is statistically significant at the 1% level. In contrast, the coefficient is small and not statistically significant for firms that operate in more than four U.S. states. Finding a coefficient that is over six times smaller for firms that cannot be tied to one or a few U.S. locations relative to firms that are closer to local reinforces the interpretation that local newspapers contain information about *local* firms.<sup>18</sup>

## 5.2 Heterogeneity over the business cycle

To further understand the mechanism driving our results, we examine whether the reduction in idiosyncratic risk following non-distress-driven newspaper closures varies over the business cycle. [Garcia \(2013\)](#) shows that financial news articles predict stock returns, but this predictive power concentrates in recessions. In Table 10, we interact the indicator variable for non-distress-driven newspaper closures with an indicator for the closure occurring during

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<sup>18</sup>Using an alternative cutoff, we find that the coefficient is almost twice as large (-2.6) for firms that operate in only one U.S. state as opposed to multiple states (-1.4). These results are untabulated.

NBER recessions. We find that the decrease in return volatility and idiosyncratic risk after non-distress-driven newspaper closures is much more pronounced in recessions. The coefficient estimate of -3.38 for idiosyncratic risk (column 2) is more than twice as large as the baseline estimate of -1.23 in Table 3. Non-distress-driven newspaper closures also predict a significant reduction in volatility outside of recessions, but the effect is less significant both statistically and economically. In light of the results of [Garcia \(2013\)](#), our evidence of heterogeneity over the business cycle suggests that investor information processing is driving the patterns we document.

## 6 Additional tests

### 6.1 Other measures of information processing

While stock return volatility is an important outcome variable in its own right and easy to interpret, we present further evidence to support the claim that distress-driven vs. other local newspaper closures lead to different patterns in investor information processing. Table 11 shows results from the same differences-in-differences specifications as before using the number of tweets (e.g., [Chen and Hwang \(2022\)](#)) and EDGAR downloads ([Drake, Roulstone, and Thornock \(2015\)](#)) to measure investor information processing. Columns 1-3 show that there is no significant change in the number of tweets, retweets, and EDGAR downloads following distress-driven newspaper closures. However, there is a significant drop in all three measures following non-distress-driven newspaper closures. Columns 4 and 5 study changes in attention, measured as the yearly average of firm-specific messages per day, and disagreement, constructed as the yearly average of the standard deviation of sentiment for a given firm-day, using StockTwits data from [Cookson, Lu, Mullins, and Niessner \(2024\)](#). We

find some evidence for an increase in attention after distress-driven closures, and a decrease after non-distress-driven ones (column 4). Column 5 shows an increase in disagreement after distress-driven closures, while the coefficient on non-distress-driven closures is negative, yet small and statistically insignificant.<sup>19</sup>

## 6.2 Firm communication with investors

Do firms communicate differently with investors after the closure of a local newspaper? To answer this question, we use company website disclosure from [Boulland, Bourveau, and Breuer \(2021\)](#) as a measure of the amount of information supplied by the firm. Table 11 column 6 shows that the total size of a firm’s website (in bytes) increases significantly after non-distress-driven newspaper closure, but not after distress-driven newspaper closures. Changes in website contents may reflect changes to the firm’s operations. To ensure that this explanation is not driving the results, Table 11 column 7 uses the total size of investor relations content as the dependent variable. We find an even larger coefficient for non-distress-driven closures, while the coefficient for distress-driven closures remains not statistically significant and even has a negative sign. Firms make more information available to investors on their website after non-distress-driven newspaper closures suggesting that they may try to make up for the information loss following these newspaper closures.

## 6.3 Corporate fraud

To further illustrate the importance of tracking the reason for newspaper closures, we use our approach and sample to examine the effect of distress-driven and non-distress-driven

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<sup>19</sup>Internet Appendix Table A7 uses news articles from Ravenpack to examine whether media coverage of the firm changes following newspaper closures. We find some evidence of a reduction in media coverage for non-distress-related media closures, yet not for distress-related closures.

local newspaper closures on corporate fraud. This analysis follows the work of [Heese et al. \(2021\)](#), with a few important differences. First and most importantly, we separate local newspaper closures into distress-driven and non-distress-driven events, as before. Second, we apply the stacked differences-in-differences method of [Goodman-Bacon \(2021\)](#) for more reliable inference. Third, our sample ends in 2021, four years later than their period of analysis. Fourth, they have precise information on plant location at the ZIP code level, which we lack: therefore, we aggregate violations at the firm level, effectively assuming that all violations occur at the headquarter ZIP code. In spite of these differences, our results are similar to theirs for the pooled sample, even if the magnitudes cannot be compared directly.

Table A8 columns 1-2 show that the number of legal violations by local firms increases following local newspaper closures, consistent with [Heese et al. \(2021\)](#). However, column 3 shows that this increase in the number of legal violations is statistically significant only after non-distress-driven newspaper closures, and is twice as large for non-distress-driven closures as compared to distress-driven closures. These findings reinforce the importance of considering the reason for local newspaper closures: doing so in the case of corporate fraud raises the point estimate and highlights that the true treatment effect may be larger than previously documented.

## 7 Conclusion

Academics and commentators have been sounding the alarm bells over the disappearance of local newspapers. This paper studies the effect of local newspaper closures on the market for local firms' shares, taking into account that newspaper closures are not random, and many are distress-driven. We use a hand-collected dataset of local newspaper closures from the most

recent two decades, coupled with a narrative classification of the reasons for each closure. We separate distress-driven newspaper closures from those occurring for other reasons. Doing so allows us to make progress on separating the selection effect of which newspapers are closed and the treatment effect of a newspaper closure on the market for local stocks.

We find that at least 29% of local newspaper closures are distress-driven. Volatility, trading activity, and liquidity move in the opposite direction after distress-driven vs. non-distress-driven local newspaper closures. Non-distress-driven newspaper closures predict a significant reduction in return volatility and idiosyncratic volatility. In contrast, distress-driven newspaper closures predict increases in both volatility measures. We infer that both selection and treatment effects are present, and the two have the opposite sign: closing a newspaper alone causes volatility to increase, whereas newspapers tend to close in areas with increasing return volatility. We find similar patterns for trading activity and liquidity. Missing information on the different reasons for newspaper closures and estimating the same empirical model would lead to an attenuation of the treatment effect by 41-43%. Last, we find substantial heterogeneity in the treatment effect, consistent with information frictions: Newspaper closures that are not distress-driven are followed by a larger drop in volatility for small stocks, growth stocks, firms in sparsely populated or rural areas, and during recessions.

Overall, our results highlight the importance of separating selection and treatment effects when studying the effect of media on financial markets, and show that local newspapers are an important source of information for investors. Our findings suggest that experts may be right to be worried about the wave of local newspaper closures over the last two decades because local investors use newspapers to process information about the firms in their area. Once we account for the selection effect of which newspapers are closed, the effect of local newspaper closures may be larger than previously documented.

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Figure 1: Closures over Time

This figure shows the number of newspaper closures by motive over the sample period. Information on newspaper closure dates and reasons are collected from Chronicling America, the U.S. News Desert database ([usnewsdeserts.com](http://usnewsdeserts.com)), WorldCat.Org, regional newspaper archives and libraries, local websites, and blogs. Our sample covers the period 2001-2021.

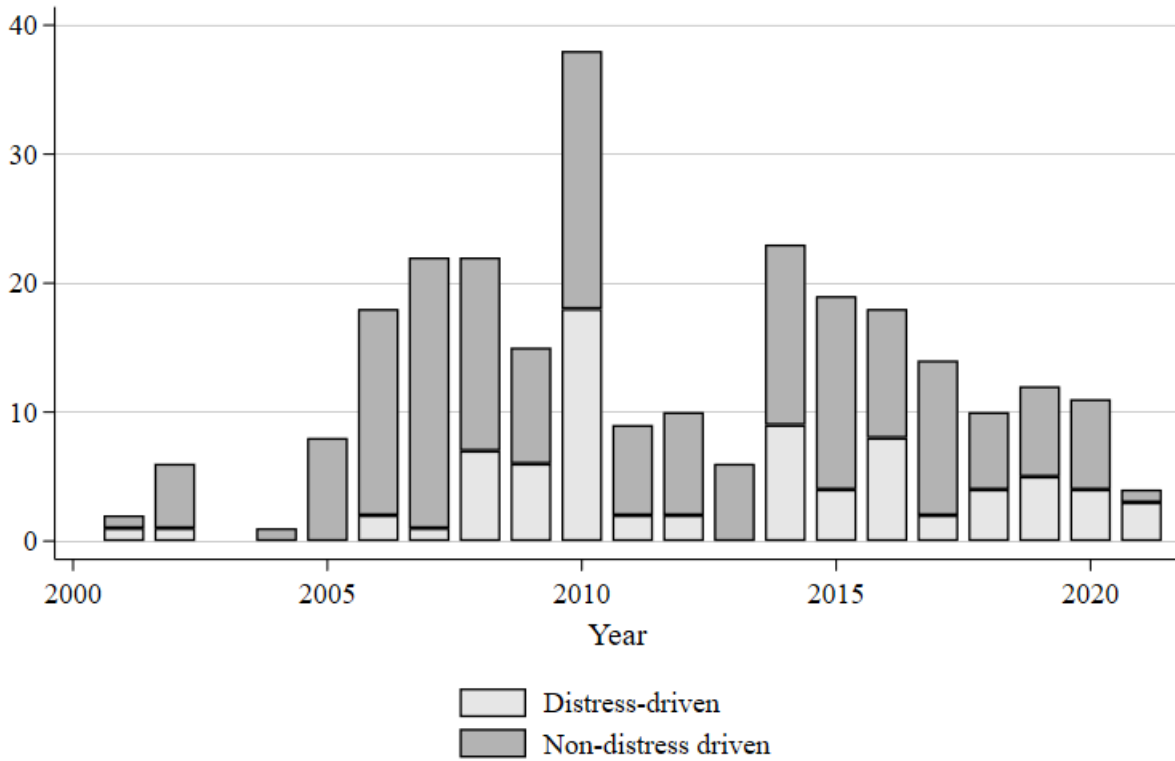
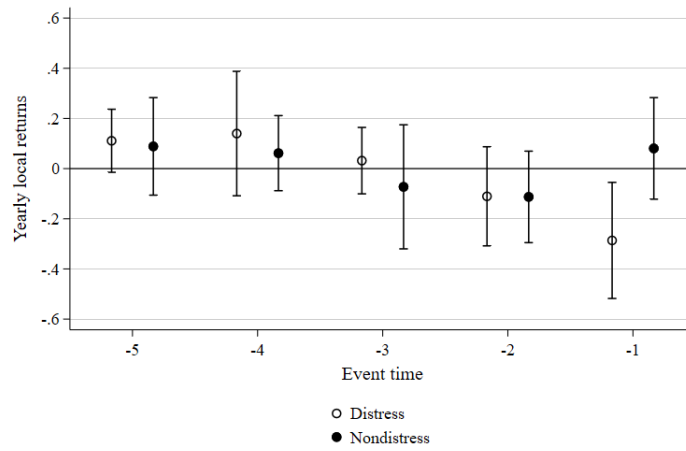


Figure 2: Pre-event local returns prior to newspaper closures

This figure plots equally-weighted yearly stock returns of firms within a 250 mile-radius around the ZIP code of a newspaper closure in the 5 years prior to the closure for distress-driven closures (indicated with hollow circles) and non-distress-driven closures (indicated with solid circles). The graph shows 95% confidence intervals around the coefficient estimate. Panel A uses stock returns of firms located within the 250-mile radius around the center of a ZIP code. Panel B restricts attention to ZIP codes with a minimum number of 20 firms within the 250-miles radius.

*Panel A: Baseline result*



*Panel B: Minimum of 20 firms*

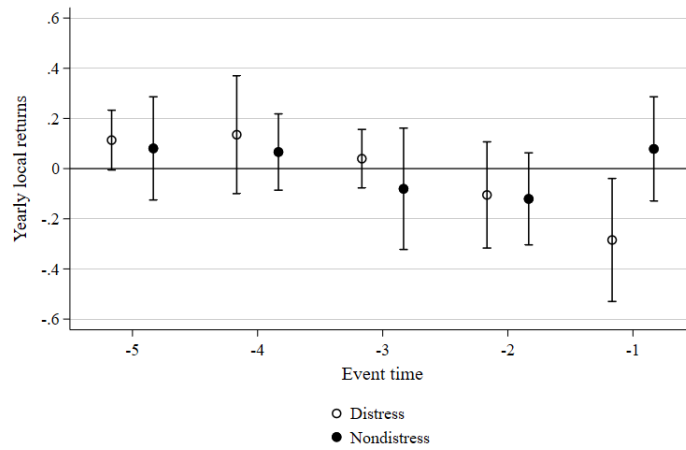


Figure 3: Idiosyncratic volatility around newspaper closures in event-time

This figure plots the coefficient of  $\beta$  from equation 1 over years around the newspaper closure. Panel A shows the estimates for the baseline results and Panel B for matched firms that differ for distress-driven and non-distress-driven closures. The hollow circle markers indicate the coefficient for distress-driven closures, and the solid circle markers indicate the coefficient for non-distress-driven closures.

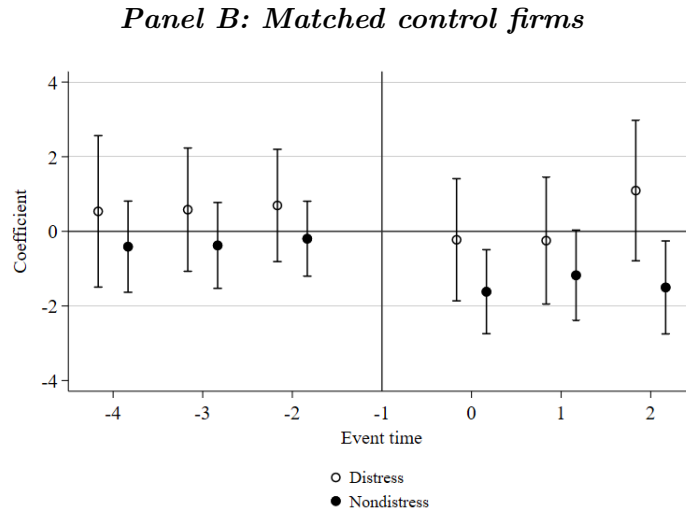
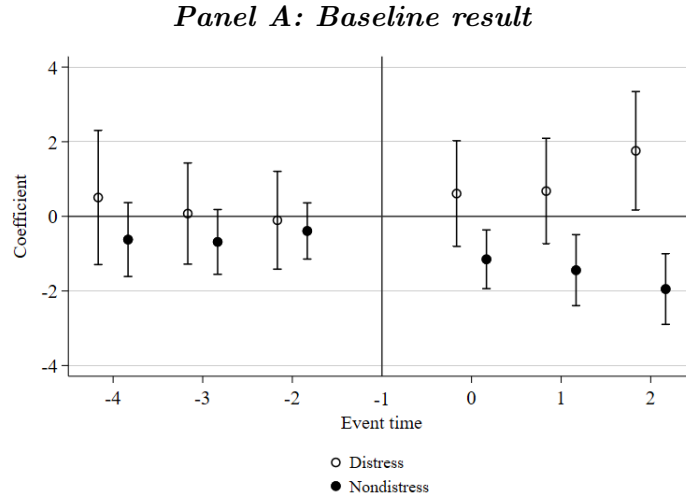


Table 1: Summary statistics of newspaper closures and affected firms

Panel A shows the number of distress and non-distress-driven local newspaper closures, and the number of publicly listed firms headquartered in ZIP codes affected by these closures each year during our sample period. Panel B shows summary statistics for affected and never-affected firms at time  $t - 1$  around the closure event. A firm is affected by a newspaper closure if it is headquartered in a ZIP code that experiences a newspaper closure. Information on newspaper closure dates and reasons are collected from Chronicling America, the U.S. News Desert Project database (usnewsdeserts.com), WorldCat.Org, regional newspaper archives and libraries, local websites, and blogs. Our sample covers the period 2001-2021.

***Panel A: Distress and non-distress-driven newspaper closures***

| Year  | Total      |       | Distress   |       | Non-distress |       |
|-------|------------|-------|------------|-------|--------------|-------|
|       | Newspapers | Firms | Newspapers | Firms | Newspapers   | Firms |
| 2001  | 1          | 37    | 0          | 36    | 1            | 1     |
| 2002  | 6          | 73    | 1          | 43    | 5            | 30    |
| 2003  | 0          | 0     | 0          | 0     | 0            | 0     |
| 2004  | 1          | 19    | 0          | 0     | 1            | 18    |
| 2005  | 8          | 162   | 0          | 0     | 8            | 162   |
| 2006  | 19         | 226   | 2          | 50    | 17           | 176   |
| 2007  | 21         | 278   | 1          | 1     | 20           | 277   |
| 2008  | 20         | 473   | 6          | 53    | 14           | 420   |
| 2009  | 17         | 115   | 6          | 72    | 11           | 43    |
| 2010  | 38         | 513   | 16         | 238   | 22           | 275   |
| 2011  | 10         | 115   | 2          | 10    | 8            | 105   |
| 2012  | 10         | 106   | 2          | 2     | 8            | 104   |
| 2013  | 4          | 106   | 0          | 0     | 4            | 106   |
| 2014  | 24         | 307   | 10         | 267   | 14           | 40    |
| 2015  | 17         | 441   | 4          | 114   | 13           | 327   |
| 2016  | 18         | 92    | 8          | 38    | 10           | 54    |
| 2017  | 14         | 334   | 2          | 20    | 12           | 314   |
| 2018  | 9          | 23    | 3          | 9     | 6            | 14    |
| 2019  | 10         | 159   | 5          | 46    | 5            | 113   |
| 2020  | 12         | 87    | 5          | 46    | 7            | 41    |
| 2021  | 4          | 52    | 3          | 51    | 1            | 1     |
| Total | 263        | 3,717 | 76         | 1,096 | 187          | 2,621 |

Table 1: Summary statistics of newspaper closures and affected firms (continued)

*Panel B: Affected and never-affected firms*

|                      | Affected |       |        | Control |       |       |
|----------------------|----------|-------|--------|---------|-------|-------|
|                      | Median   | Mean  | S.D.   | Median  | Mean  | S.D.  |
| Total assets         | 704      | 5,116 | 11,594 | 548     | 2,793 | 7,524 |
| Market cap           | 623      | 3,725 | 8,367  | 289     | 1,906 | 5,387 |
| R&D scaled by assets | 0.00     | 0.05  | 0.11   | 0.00    | 0.04  | 0.09  |
| Tobin's Q'           | 1.42     | 2.00  | 1.64   | 1.23    | 1.73  | 1.41  |
| Profitability        | 0.08     | 0.02  | 0.24   | 0.08    | 0.05  | 0.20  |
| Leverage             | 0.12     | 0.18  | 0.19   | 0.10    | 0.17  | 0.18  |
| Sales growth         | 0.07     | 0.15  | 0.51   | 0.06    | 0.13  | 0.43  |
| Return volatility    | 40.01    | 48.09 | 31.29  | 42.68   | 53.05 | 34.82 |
| Systematic risk      | 14.93    | 17.60 | 12.29  | 14.31   | 17.03 | 12.68 |
| Idiosyncratic risk   | 34.79    | 43.26 | 30.79  | 37.85   | 48.63 | 34.64 |
| $R^2$                | 17.37    | 20.84 | 17.48  | 11.66   | 18.12 | 18.12 |
| Market beta          | 0.86     | 0.85  | 0.52   | 0.77    | 0.76  | 0.55  |
| Turnover             | 0.59     | 0.82  | 0.84   | 0.39    | 0.63  | 0.76  |
| Amihud illiquidity   | 0.02     | 2.40  | 9.29   | 0.15    | 4.45  | 12.29 |
| Zero return fraction | 0.00     | 0.05  | 0.29   | 0.00    | 0.10  | 0.38  |
| Observations         | 3,599    |       |        | 33,786  |       |       |

Table 2: Closure motives

The table below shows the breakdown of distress and non-distress-driven closure motives. Information on newspaper closure dates and reasons are collected from Chronicling America, the U.S. News Desert database (usnewsdeserts.com), WorldCat.Org, regional newspaper archives and libraries, local websites, and blogs. Our sample covers the period 2001-2021.

| Motives                           | Closures |
|-----------------------------------|----------|
| Distress-driven                   | 76       |
| Financial distress                | 48       |
| Financial distress-related merger | 28       |
| Non-distress-driven               | 187      |
| Within group consolidation        | 56       |
| Merger not related to distress    | 49       |
| Personal reasons                  | 7        |
| Other                             | 84       |
| Total                             | 263      |

Table 3: Distress and non-distress closures and investor information processing

This table regresses stock return volatility, idiosyncratic volatility, and systematic risk on closure indicators, the natural logarithm of market capitalization, Tobin's Q, sales growth, leverage, profitability and R&D scaled by total assets as firm-level control variables, stack fixed effects interacted with firm fixed effects, and stack fixed effects interacted with year fixed effects on the sample of affected firms and for each event-year stack never-affected firms around the event year as control subjects. Panel A separates distress-driven and non-distress-driven closures, while Panel B pools all newspaper closures. Coefficients on control variables are reported in Table A3 in the Appendix. Standard errors are clustered at firm level, and shown in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, or 1% level respectively.

| <i>Panel A: Separating distress-driven and non-distress-driven closures</i> |                          |                           |                        |
|-----------------------------------------------------------------------------|--------------------------|---------------------------|------------------------|
|                                                                             | Return volatility<br>(1) | Idiosyncratic risk<br>(2) | Systematic risk<br>(3) |
| Post distress closure                                                       | 1.475**<br>(0.588)       | 1.413**<br>(0.573)        | 0.183<br>(0.278)       |
| Post non-distress closure                                                   | -1.353***<br>(0.415)     | -1.234***<br>(0.394)      | -0.501**<br>(0.196)    |
| Stack $\times$ firm FE                                                      | Yes                      | Yes                       | Yes                    |
| Stack $\times$ year FE                                                      | Yes                      | Yes                       | Yes                    |
| Adjusted $R^2$                                                              | 0.713                    | 0.724                     | 0.674                  |
| N                                                                           | 371,434                  | 371,434                   | 371,434                |
| <i>Panel B: Pooling all closures, irrespective of closure reason</i>        |                          |                           |                        |
|                                                                             | Return volatility<br>(1) | Idiosyncratic risk<br>(2) | Systematic risk<br>(3) |
| Post closure                                                                | -0.793**<br>(0.386)      | -0.709*<br>(0.367)        | -0.378**<br>(0.183)    |
| Controls                                                                    | Yes                      | Yes                       | Yes                    |
| Stack $\times$ firm FE                                                      | Yes                      | Yes                       | Yes                    |
| Stack $\times$ year FE                                                      | Yes                      | Yes                       | Yes                    |
| Adjusted $R^2$                                                              | 0.713                    | 0.724                     | 0.674                  |
| N                                                                           | 371,434                  | 371,434                   | 371,434                |

Table 4: Distress and non-distress closures and investor information processing: matched control firms

This table repeats the regressions from Table 3 while using different matched samples for the set of firms affected by distress-driven newspaper closures and non-distress-driven newspaper closures. Panel A shows the comparison of firm characteristics of firms affected by distress-driven closures and non-distress-driven closures in  $t - 1$  around the closure. The matched firms are selected using Mahalanobis distance matching on the following covariates: the natural logarithm of market capitalization, Tobin's Q, sales growth, leverage, profitability and R&D scaled by total assets. Standard errors are clustered at firm level, and given in parentheses. \*, \*\*\*, and \*\*\* indicate statistical significance at the 10%, 5%, or 1% level respectively.

*Panel A: Comparison between firms affected by distress and non-distress closures*

|                         | Distress |        | Non-distress |        | Comparison |        |
|-------------------------|----------|--------|--------------|--------|------------|--------|
|                         | Mean     | S.D.   | Mean         | S.D.   | Difference | t-test |
| Total assets            | 8,312    | 23,780 | 6,972        | 22,195 | -2,022.9   | -2.47  |
| Market capitalization   | 4,976    | 13,319 | 4,725        | 13,293 | -533.9     | -1.09  |
| RD scaled by assets     | 0.04     | 0.10   | 0.06         | 0.12   | 0.02       | 5.49   |
| Tobin's Q               | 1.77     | 1.43   | 2.05         | 1.69   | 0.31       | 4.95   |
| Profitability           | 0.03     | 0.22   | 0.01         | 0.25   | -0.02      | -1.63  |
| Leverage                | 0.20     | 0.19   | 0.18         | 0.20   | -0.02      | -2.63  |
| Sales growth            | 0.09     | 0.47   | 0.16         | 0.53   | 0.07       | 3.74   |
| Total return volatility | 52.74    | 38.14  | 46.23        | 29.51  | -6.31      | -5.35  |
| Systematic risk         | 20.54    | 16.06  | 16.37        | 10.54  | -3.98      | -8.65  |
| Idiosyncratic risk      | 46.47    | 37.11  | 41.97        | 29.32  | -4.36      | -3.75  |
| Market beta             | 0.83     | 0.53   | 0.85         | 0.53   | 0.03       | 1.58   |
| $R^2$                   | 23.18    | 20.04  | 19.97        | 16.59  | -3.18      | -4.81  |

Table 4: Distress and non-distress closures and investor information processing: matched control firms (continued)

*Panel B: Information processing with matched controls*

|                           | Return volatility   | Idiosyncratic risk  | Systematic risk   |
|---------------------------|---------------------|---------------------|-------------------|
|                           | (1)                 | (2)                 | (3)               |
| Post distress closure     | 0.176<br>(0.646)    | 0.286<br>(0.615)    | -0.112<br>(0.335) |
| Post non-distress closure | -1.210**<br>(0.547) | -1.234**<br>(0.519) | -0.184<br>(0.262) |
| Controls                  | Yes                 | Yes                 | Yes               |
| Stack $\times$ firm FE    | Yes                 | Yes                 | Yes               |
| Stack $\times$ year FE    | Yes                 | Yes                 | Yes               |
| Adjusted $R^2$            | 0.710               | 0.721               | 0.678             |
| Obs                       | 55,614              | 55,614              | 55,614            |

Table 5: Distress and non-distress-driven newspaper closures, trading activity, and liquidity

This table shows the regression of log turnover, [Amihud \(2002\)](#) illiquidity, and the fraction of zero return days ([Lesmond et al. \(1999\)](#)) on a variable that is set to 1 for affected firms after a distress-driven closure and to zero otherwise, on a dummy variable set to 1 after a non-distress-driven closure and to zero otherwise, the natural logarithm of market capitalization, Tobin's Q, sales growth, leverage, profitability and R&D scaled by total assets as firm-level control variables, stack-specific firm fixed effects interacted, and stack fixed effects interacted with year fixed effects on the sample of affected firms and for each event-year stack never-affected firms around the event year as control subjects in columns 1 to 3. Standard errors are clustered at firm level, and given in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, or 1% level respectively.

|                           | Log turnover<br>(1)  | Amihud<br>(2)       | Zero return fraction<br>(3) |
|---------------------------|----------------------|---------------------|-----------------------------|
| Post distress closure     | -0.022<br>(0.022)    | -0.121<br>(0.250)   | -0.002<br>(0.007)           |
| Post non-distress closure | -0.068***<br>(0.015) | 0.454***<br>(0.156) | 0.009**<br>(0.004)          |
| Stack $\times$ firm FE    | Yes                  | Yes                 | Yes                         |
| Stack $\times$ year FE    | Yes                  | Yes                 | Yes                         |
| Adjusted $R^2$            | 0.741                | 0.674               | 0.262                       |
| N                         | 510,938              | 409,286             | 535,879                     |

Table 6: Tighter time intervals and controlling for time-varying heterogeneity at the state-level

This table repeats the regressions from Table 3 while using tighter intervals of -3 to +3 years around the event year (Panel A) and adding state  $\times$  year fixed effects (Panel B). Standard errors are clustered at firm level, and given in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, or 1% level respectively.

| <i>Panel A: Controlling for state <math>\times</math> year fixed effects</i> |                    |                     |                  |
|------------------------------------------------------------------------------|--------------------|---------------------|------------------|
|                                                                              | Return volatility  | Idiosyncratic risk  | Systematic risk  |
|                                                                              | (1)                | (2)                 | (3)              |
| Post distress closure                                                        | 2.092**<br>(0.833) | 2.091**<br>(0.824)  | 0.252<br>(0.405) |
| Post non-distress closure                                                    | -1.080*<br>(0.627) | -1.364**<br>(0.596) | 0.223<br>(0.298) |
| Controls                                                                     | Yes                | Yes                 | Yes              |
| Stack $\times$ firm FE                                                       | Yes                | Yes                 | Yes              |
| Stack $\times$ state $\times$ year FE                                        | Yes                | Yes                 | Yes              |
| Adjusted $R^2$                                                               | 0.713              | 0.724               | 0.674            |
| N                                                                            | 371,434            | 371,434             | 371,434          |

| <i>Panel B: Tighter time interval of -3 to +3 years</i> |                      |                      |                   |
|---------------------------------------------------------|----------------------|----------------------|-------------------|
|                                                         | Return volatility    | Idiosyncratic risk   | Systematic risk   |
|                                                         | (1)                  | (2)                  | (3)               |
| Post distress closure                                   | 1.001<br>(0.710)     | 1.076<br>(0.679)     | -0.036<br>(0.356) |
| Post non-distress closure                               | -1.400***<br>(0.408) | -1.388***<br>(0.395) | -0.209<br>(0.198) |
| Controls                                                | Yes                  | Yes                  | Yes               |
| Stack $\times$ firm FE                                  | Yes                  | Yes                  | Yes               |
| Stack $\times$ year FE                                  | Yes                  | Yes                  | Yes               |
| Adjusted $R^2$                                          | 0.739                | 0.745                | 0.718             |
| N                                                       | 204,341              | 204,341              | 204,341           |

Table 7: Attenuation for different model specifications and dependent variables

This table summarizes the attenuation across different models using idiosyncratic risk as an outcome variable (Panel A) and using different outcome variables (Panel B). Column 1 shows attenuation in percent, calculated as the difference in the coefficient of *Post non-distress-driven*, reported in column 2, and the coefficient of the pooled variable *Post closure*, reported in column 3, which captures both distress and non-distress-driven closures, scaled by the coefficient of *Post non-distress-driven*.

|                                            | Attenuation (%) | Coefficient on post closure |        |
|--------------------------------------------|-----------------|-----------------------------|--------|
|                                            |                 | Non-distress                | Pooled |
|                                            | (1)             | (2)                         | (3)    |
| <b><i>Panel A: By model</i></b>            |                 |                             |        |
| Baseline                                   | 42.5            | -1.234                      | -0.709 |
| State $\times$ year FE                     | 62.0            | -1.364                      | -0.518 |
| Tighter interval (-3 to +3)                | 32.2            | -1.388                      | -0.941 |
| Matching                                   | 30.2            | -1.065                      | -0.743 |
| <b><i>Panel B: By outcome variable</i></b> |                 |                             |        |
| Total volatility                           | 41.4            | -1.353                      | -0.793 |
| Idiosyncratic risk                         | 42.5            | -1.234                      | -0.709 |
| Systematic risk                            | 24.6            | -0.501                      | -0.378 |
| Log turnover                               | 11.6            | -0.068                      | -0.060 |
| Amihud illiquidity                         | 25.5            | 0.454                       | 0.338  |
| Zero return fraction                       | 17.8            | 0.009                       | 0.007  |

Table 8: Heterogeneity in information processing across firms

This table repeats the regressions from Table 3 Panel B, while interacting the dummy variables set to 1 after non-distress-driven closures with a dummy indicating that the respective firm is above the median of a certain firm characteristic, and, separately, with a dummy variable indicating that the firm has a value below the median. Column 1 splits the sample at the median value of market capitalization, column 2 at the median of the industry-level sales volatility, column 3 at the median of Tobin's Q, column 4 at the median of non-missing advertising expenditures scaled by total assets, column 5 at the median value of the number of yearly Dow Jones news articles, column 6 splits the sample at the median Google attention, and controls for a dummy variable indicating missing Google search data and its interaction with the post non-distress driven closure as control variables. Standard errors are clustered at firm level, and given in parentheses. \*, \*\*\*, and \*\*\* indicate statistical significance at the 10%, 5%, or 1% level respectively.

| Sample split by                         | Idiosyncratic risk   |                      |                      |                      |                      |                      |
|-----------------------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
|                                         | Market cap<br>(1)    | Sales vola<br>(2)    | Tobin's Q<br>(3)     | Advertising<br>(4)   | Media<br>(5)         | Google<br>(6)        |
| Post distress closure                   | 1.374**<br>(0.572)   | 1.361**<br>(0.574)   | 1.390**<br>(0.574)   | 1.963**<br>(0.851)   | 1.424**<br>(0.573)   | 1.396**<br>(0.573)   |
| Post non-distress closure $\times$ low  | -2.370***<br>(0.631) | 0.116<br>(0.524)     | -0.349<br>(0.526)    | -0.462<br>(0.843)    | -2.083***<br>(0.579) | -4.373***<br>(0.644) |
| Post non-distress closure $\times$ high | -0.353<br>(0.371)    | -2.238***<br>(0.509) | -2.035***<br>(0.430) | -2.132***<br>(0.668) | -0.960**<br>(0.392)  | -0.569<br>(0.525)    |
| Controls                                | Yes                  | Yes                  | Yes                  | Yes                  | Yes                  | Yes                  |
| Stack $\times$ firm FE                  | Yes                  | Yes                  | Yes                  | Yes                  | Yes                  | Yes                  |
| Stack $\times$ year FE                  | Yes                  | Yes                  | Yes                  | Yes                  | Yes                  | Yes                  |
| Adjusted $R^2$                          | 0.724                | 0.724                | 0.724                | 0.719                | 0.724                | 0.724                |
| N                                       | 371,434              | 371,434              | 371,434              | 169,654              | 371,434              | 371,434              |

Table 9: Geographic heterogeneity in information processing

This table repeats the regressions from Table 3 Panel B, while interacting the dummy variables set to 1 after non-distress-driven closures with a dummy indicating a certain geographical feature. Low in column 1 indicates that the firm is not located in one of the top 10 metropolitan areas in the U.S., high indicates that the firm is located in one of those areas. Low in column 2 indicates that the firm is located in an area with a population of less than 750 people per square mile, and high indicates the firm is located in an area with a greater density. The corresponding density thresholds in columns 3 and 4 are 1,000 and 2,000. Column 5 splits the sample into firms with low geographic dispersion (geographic presence in up to three U.S. states) and high geographic dispersion (four or more U.S. states). Standard errors are clustered at firm level, and given in parentheses. \*, \*\*\*, and \*\*\* indicate statistical significance at the 10%, 5%, or 1% level respectively.

| Sample split by                         | Idiosyncratic risk   |                      |                      |                      |                      |
|-----------------------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
|                                         | Metro area<br>(1)    | Density 750<br>(2)   | Density 1000<br>(3)  | Density 2000<br>(4)  | Dispersion<br>(5)    |
| Post distress closure                   | 1.394**<br>(0.573)   | 1.418**<br>(0.573)   | 1.411**<br>(0.573)   | 1.400**<br>(0.573)   | 1.388**<br>(0.574)   |
| Post non-distress closure $\times$ low  | -1.746***<br>(0.432) | -2.364***<br>(0.719) | -2.277***<br>(0.615) | -1.593***<br>(0.461) | -3.056***<br>(0.659) |
| Post non-distress closure $\times$ high | 1.012<br>(0.751)     | -0.906**<br>(0.438)  | -0.726<br>(0.464)    | -0.694<br>(0.611)    | -0.473<br>(0.424)    |
| Controls                                | Yes                  | Yes                  | Yes                  | Yes                  | Yes                  |
| Stack $\times$ firm FE                  | Yes                  | Yes                  | Yes                  | Yes                  | Yes                  |
| Stack $\times$ year FE                  | Yes                  | Yes                  | Yes                  | Yes                  | Yes                  |
| Adjusted $R^2$                          | 0.724                | 0.724                | 0.724                | 0.724                | 0.724                |
| N                                       | 371,434              | 371,434              | 371,434              | 371,434              | 371,434              |

Table 10: Heterogeneity in information processing over the business cycle

This table repeats the regressions from Table 3 Panel B, while interacting the distress and non-distress-driven closure dummy variables with an indicator for NBER recessions. Standard errors are clustered at firm level, and given in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, or 1% level respectively.

|                                                 | Return volatility    | Idiosyncratic risk   | Systematic risk      |
|-------------------------------------------------|----------------------|----------------------|----------------------|
|                                                 | (1)                  | (2)                  | (3)                  |
| Post distress closure $\times$ recession        | -0.173<br>(1.362)    | 0.052<br>(1.354)     | -0.289<br>(0.621)    |
| Post non-distress closure $\times$ recession    | -3.856***<br>(0.871) | -3.376***<br>(0.840) | -1.585***<br>(0.373) |
| Post distress closure $\times$ no recession     | 1.844***<br>(0.633)  | 1.714***<br>(0.612)  | 0.267<br>(0.305)     |
| Post non-distress closure $\times$ no recession | -0.860*<br>(0.441)   | -0.812*<br>(0.418)   | -0.283<br>(0.213)    |
| Controls                                        | Yes                  | Yes                  | Yes                  |
| Stack $\times$ firm FE                          | Yes                  | Yes                  | Yes                  |
| Stack $\times$ year FE                          | Yes                  | Yes                  | Yes                  |
| Adjusted $R^2$                                  | 0.713                | 0.724                | 0.674                |
| N                                               | 371,434              | 371,434              | 371,434              |

Table 11: Distress and non-distress-driven newspaper closures and other proxies of investor information processing

This table shows the results of Poisson pseudo-maximum likelihood regressions of certain count-like outcome variables on a dummy variable that is set to 1 for affected firms after a distress-driven closure and to zero otherwise, on a dummy variable set to 1 after a non-distress-driven closure and to zero otherwise, the natural logarithm of market capitalization, Tobin's Q, sales growth, leverage, profitability and R&D scaled by total assets as firm-level control variables, stack-specific firm fixed effects interacted, and stack fixed effects interacted with year fixed effects on the sample of affected firms and for each event-year stack never-affected firms around the event year as control subjects in columns 1 to 3. Column 1 uses the number of yearly tweets on the firm, column 2 the number of yearly retweets, using the data provided by [Chen and Hwang \(2022\)](#). Column 3 uses the number of yearly EDGAR logs as an outcome variable. Columns 4 and 5 estimate OLS regressions with the same set of independent variables, using yearly measures of Attention, proxied for by the number of messages, and Disagreement, measured by the standard deviation of sentiment across messages for a given firm-day, constructed using StockTwits data from [Cookson and Niessner \(2024\)](#) as outcome variables. Columns 6 and 7 use yearly data on the natural logarithm of the company web size that can be classified into contents in Bytes and the Investor Relations contents in Bytes from [Boulland et al. \(2021\)](#). Standard errors are clustered at firm level, and given in parentheses. \*, \*\*\*, and \*\*\* indicate statistical significance at the 10%, 5%, or 1% level respectively.

| Estimation                | Tweets<br>PPML       | Retweets<br>PPML   | EDGAR<br>PPML       | Attention<br>PPML  | Disagreement<br>OLS | Web size<br>OLS    | IR web size<br>OLS |
|---------------------------|----------------------|--------------------|---------------------|--------------------|---------------------|--------------------|--------------------|
| Data frequency            | Year                 | Year               | Year                | Year               | Year                | Year               | Year               |
|                           | (1)                  | (2)                | (3)                 | (4)                | (5)                 | (6)                | (7)                |
| Post distress closure     | -0.078<br>(0.057)    | -0.100<br>(0.124)  | -0.034<br>(0.034)   | 0.613*<br>(0.328)  | 0.037***<br>(0.014) | 0.121<br>(0.095)   | 0.088<br>(0.092)   |
| Post non-distress closure | -0.143***<br>(0.037) | -0.140*<br>(0.076) | -0.052**<br>(0.027) | -0.521*<br>(0.281) | -0.004<br>(0.013)   | 0.158**<br>(0.062) | 0.148**<br>(0.062) |
| Stack $\times$ firm FE    | Yes                  | Yes                | Yes                 | Yes                | Yes                 | Yes                | Yes                |
| Stack $\times$ year FE    | Yes                  | Yes                | Yes                 | Yes                | Yes                 | Yes                | Yes                |
| Adjusted $R^2$            |                      |                    |                     | 0.407              | 0.118               | 0.529              | 0.471              |
| N                         | 78,185               | 78,126             | 218,456             | 17,329             | 9,152               | 206,905            | 188,568            |

Table A1: Variable definitions

This table shows variable definitions of pricing outcomes, closure variables, firm characteristics, and geographical characteristics.

| Variable                            | Definition                                                                                                                                                                                                  | Source                                     |
|-------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------|
| <i>Pricing outcomes</i>             |                                                                                                                                                                                                             |                                            |
| Return volatility                   | The variance of daily stock returns over a full calendar year.                                                                                                                                              | CRSP                                       |
| Idiosyncratic risk                  | Standard deviation of residuals from a regression of daily excess returns on the Fama-French 3 factors for the full calendar year                                                                           | CRSP                                       |
| Systematic risk                     | Standard deviation of predicted returns from a regression of daily excess returns on the Fama-French 3 factors for the full calendar year                                                                   | CRSP                                       |
| Market beta                         | Coefficient on the market premium from a regression of daily excess returns on the Fama-French 3 factors for the full calendar year                                                                         | CRSP                                       |
| R-squared                           | Share of predicted variation from a regression of daily excess returns on the Fama-French 3 factors for the full calendar year                                                                              | CRSP                                       |
| <i>Closure variables</i>            |                                                                                                                                                                                                             |                                            |
| Post closure                        | Dummy equal to 1 if firm is affected by a newspaper closure, 0 otherwise                                                                                                                                    | Manual                                     |
| Post distress closure               | Dummy equal to 1 if firm is affected by a distress-driven newspaper closure, 0 otherwise                                                                                                                    | Manual search                              |
| Post nondistress closure            | Dummy equal to 1 if firm is affected by a non-distress-driven newspaper closure, 0 otherwise                                                                                                                | Manual                                     |
| Affected                            | Dummy equal to 1 the firm has ever been affected by a distress-or non-distress-driven newspaper closure over the entire sample period, and equal to 0 otherwise                                             | Manual                                     |
| <i>Geographical characteristics</i> |                                                                                                                                                                                                             |                                            |
| Density                             | Population per square kilometer                                                                                                                                                                             | Opendatasoft<br>geographical<br>repository |
| Metro area                          | Dummy variable set to 1 if the firm is located in one of the top 10 U.S. metropolitan areas (New York City, Los Angeles, Chicago, Houston, Phoenix, Philadelphia, San Antonio, San Diego, Dallas, San Jose) | Compustat                                  |
| Violation                           | Dummy variable set to 1 if there was a violation occurring in the given ZIP code, and to 0 otherwise                                                                                                        | Violation-Tracker                          |

Table A1: Variable definitions (continued)

| Variable                    | Definition                                                                                                                           | Source    |
|-----------------------------|--------------------------------------------------------------------------------------------------------------------------------------|-----------|
| <i>Firm characteristics</i> |                                                                                                                                      |           |
| Total assets                | Book value of total assets in USD millions                                                                                           | Compustat |
| Market capitalization       | Market capitalization in USD millions                                                                                                | Compustat |
| R&D scaled by assets        | Research and development expenditures scaled by the book value of total assets                                                       | Compustat |
| Tobin's Q                   | Book value of total assets minus the book value of total equity plus market capitalization, scaled by the book value of total assets | Compustat |
| Profitability               | Operating income scaled by total assets                                                                                              |           |
| Sales growth                | Sales divided by sales in the prior fiscal year minus 1                                                                              | Compustat |
| Leverage                    | Book value of long-term liabilities plus book value of short-term liabilities scaled by the book value of total assets               | Compustat |
| Advertising                 | Advertising expenses scaled by total assets                                                                                          |           |
| Turnover                    | Average daily shares traded scaled by total shares outstanding over one quarter                                                      | CRSP      |
| Amihud                      | Average of absolute daily return scaled by the dollar volume of traded shares over one quarter in US dollar thousands                | CRSP      |
| Zero return fraction        | Share of days with a zero return scaled by the number of trading days in a quarter                                                   | CRSP      |

Table A1: Variable definitions (continued)

| Variable                           | Definition                                                                               | Source                                      |
|------------------------------------|------------------------------------------------------------------------------------------|---------------------------------------------|
| <i>Firm-level media activities</i> |                                                                                          |                                             |
| Tweets                             | Number of Tweets                                                                         | <a href="#">Chen and Hwang (2022)</a>       |
| Retweets                           | Number of Retweets                                                                       | <a href="#">Chen and Hwang (2022)</a>       |
| Attention                          | Yearly average of daily messages on StockTwits                                           | <a href="#">Cookson and Niessner (2024)</a> |
| Sentiment                          | Yearly average of standard deviation of sentiment using StockTwits at the firm-day level | <a href="#">Cookson and Niessner (2024)</a> |
| Web size                           | The size of company web site contents in Bytes                                           | <a href="#">Boulland et al. (2021)</a>      |
| IR web size                        | The size of Investor Relations web contents in Bytes                                     | <a href="#">Boulland et al. (2021)</a>      |
| News items                         | Yearly number of news items                                                              | Ravenpack                                   |
| Relevance                          | Yearly news items with relevance score of 100                                            | Ravenpack                                   |
| Novelty                            | Yearly news items with event novelty score of 100                                        | Ravenpack                                   |
| Pos (Neg)                          | Yearly news items with Composite sentiment score strictly above (below) 50               | Ravenpack                                   |
| EDGAR                              | Number of EDGAR logs                                                                     | SEC                                         |

## Internet Appendix to “Newspaper Closures and Trading in Local Stocks”

The Appendix presents additional tests referred to in the main part of the paper. Table A2 shows factors that explain firm-level news coverage. Table A3 reports the coefficient on control variables for Table 3. Table A4 studies changes in fundamental characteristics around newspaper closures, while Table A5 splits the sample according to the comovement metric by [Dávila and Parlatore \(2023\)](#). Table A6 classifies firms as affected and unaffected by a local newspaper closure based on the state-level geographic dispersion data by [Garcia and Norli \(2012\)](#). Table A7 presents how media coverage measures based on RavenPack change around newspaper closures, and Table A8 studies ZIP-level misconduct rates. Section A9 presents information about our narrative classification approach and examples for closures classified as non-distress driven and distress-driven.

Table A2: Firm-level news coverage

This table shows a regression of the number of articles on a dummy variable *Past top 10 company*, identifying the top 10 firms that covered by the newspaper in the past year, *Local*, which are set to 1 if the firm and the newspaper are located in the same state or city respectively, and to 0 otherwise. The regressions are based on a firm-newspaper-year panel of S&P 500 firms and 30 newspapers between 2010 and 2023. Standard errors are clustered at firm level, and given in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, or 1% level respectively.

|                           | Firm news coverage   |                      |                      |
|---------------------------|----------------------|----------------------|----------------------|
|                           | (1)                  | (2)                  | (3)                  |
| Past top 10 company       | 15.635***<br>(0.808) | 14.274***<br>(0.818) | 15.451***<br>(0.814) |
| Local (state)             | 0.402***<br>(0.136)  | 0.515***<br>(0.148)  | 0.421***<br>(0.134)  |
| Local (city)              | 0.888***<br>(0.323)  | 1.149***<br>(0.370)  | 0.922***<br>(0.326)  |
| Top size quintile         | 0.780***<br>(0.181)  | 0.620***<br>(0.183)  |                      |
| R&D intensity             | -12.254<br>(7.457)   | -1.208<br>(3.631)    |                      |
| Profit volatility         | -1.486**<br>(0.655)  | -1.675**<br>(0.713)  |                      |
| Sales growth              | 0.485**<br>(0.232)   | 0.129<br>(0.211)     |                      |
| Leverage                  | 0.556<br>(0.485)     | -0.664<br>(0.510)    |                      |
| Tobin's Q                 | 0.071**<br>(0.034)   | 0.036<br>(0.033)     |                      |
| Firm-initiated disclosure |                      | 0.002**<br>(0.001)   |                      |
| Source FE                 | Yes                  | Yes                  | Yes                  |
| Firm FE                   | Yes                  | Yes                  |                      |
| Year FE                   | Yes                  | Yes                  |                      |
| Year $\times$ firm FE     |                      |                      | Yes                  |
| Adjusted $R^2$            | 0.199                | 0.213                | 0.205                |
| N                         | 79,720               | 62,312               | 79,717               |

Table A3: Coefficients on control variables for Table 3

This table shows the same regressions as in Table 3, while reporting the coefficients on the control variables. Standard errors are clustered at firm level, and given in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, or 1% level respectively.

|                           | Return volatility<br>(1) | Idiosyncratic risk<br>(2) | Systematic risk<br>(3) |
|---------------------------|--------------------------|---------------------------|------------------------|
| Post distress closure     | 1.475**<br>(0.588)       | 1.413**<br>(0.573)        | 0.183<br>(0.278)       |
| Post non-distress closure | -1.353***<br>(0.415)     | -1.234***<br>(0.394)      | -0.501**<br>(0.196)    |
| Log market cap            | -10.484***<br>(0.353)    | -11.461***<br>(0.346)     | 0.623***<br>(0.150)    |
| Tobin's Q                 | 2.977***<br>(0.238)      | 2.674***<br>(0.232)       | 1.233***<br>(0.085)    |
| Sales growth              | 0.658*<br>(0.361)        | 0.634*<br>(0.357)         | 0.215*<br>(0.130)      |
| Leverage                  | 9.665***<br>(1.547)      | 9.032***<br>(1.506)       | 3.857***<br>(0.707)    |
| Profitability             | -26.544***<br>(2.338)    | -24.780***<br>(2.258)     | -5.478***<br>(0.846)   |
| R&D                       | -15.964***<br>(6.163)    | -10.879*<br>(6.081)       | -14.522***<br>(2.157)  |
| Stack $\times$ firm FE    | Yes                      | Yes                       | Yes                    |
| Stack $\times$ year FE    | Yes                      | Yes                       | Yes                    |
| Adjusted $R^2$            | 0.713                    | 0.724                     | 0.674                  |
| N                         | 371,434                  | 371,434                   | 371,434                |

Table A4: Changes in fundamental firm characteristics around newspaper closures

This table regresses firm characteristics on closure indicators for distress-driven and non-distress-driven closures controlling for stack fixed effects interacted with firm fixed effects, and stack fixed effects interacted with year fixed effects on the sample of affected firms and for each event-year stack never-affected firms around the event year as control subjects. Profit (sales) vola is the standard deviation of return on assets (sales) in the next five years. Standard errors are clustered at firm level, and given in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, or 1% level respectively.

|                           | Profitability    | Sales growth      | Tobin's Q        | Profit vola       | Sales vola         |
|---------------------------|------------------|-------------------|------------------|-------------------|--------------------|
|                           | (1)              | (2)               | (3)              | (3)               | (5)                |
| Post distress closure     | 0.001<br>(0.003) | 0.002<br>(0.010)  | 0.005<br>(0.029) | -0.001<br>(0.001) | 17.205<br>(36.262) |
| Post non-distress closure | 0.003<br>(0.002) | -0.004<br>(0.008) | 0.002<br>(0.025) | -0.001<br>(0.001) | 1.758<br>(24.487)  |
| Stack $\times$ firm FE    | Yes              | Yes               | Yes              | Yes               | Yes                |
| Stack $\times$ year FE    | Yes              | Yes               | Yes              | Yes               | Yes                |
| Adjusted $R^2$            | 0.771            | 0.183             | 0.736            | 0.749             | 0.845              |
| N                         | 371,105          | 371,105           | 371,105          | 273,981           | 275,442            |

Table A5: Accounting for the comovement between volatility and informativeness

This table shows the same regressions as in Pabel A of Table 3, suppressing the coefficients of the control variables, while sorting firms according to the comovement score by [Dávila and Parlato](#) (2023). Column 1 restricts attention to firms with a comovement score below 0.5, column 2 to firms with a comovement score above 0.5, column 3 to firms with a comovement score equal to 0, and column 4 with a comovement score equal to 1. Standard errors are clustered at firm level, and given in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, or 1% level respectively.

| Subsample of comovement score | Idiosyncratic risk |                      |                   |                     |
|-------------------------------|--------------------|----------------------|-------------------|---------------------|
|                               | < 0.5<br>(1)       | $\geq 0.5$<br>(2)    | = 0<br>(3)        | = 1<br>(4)          |
| Post distress closure         | 0.752<br>(0.730)   | 2.088***<br>(0.640)  | -2.167<br>(4.492) | 1.158<br>(2.027)    |
| Post non-distress closure     | -0.994*<br>(0.588) | -1.745***<br>(0.537) | 1.434<br>(4.825)  | -3.866**<br>(1.834) |
| Controls                      | Yes                | Yes                  | Yes               | Yes                 |
| Stack $\times$ firm FE        | Yes                | Yes                  | Yes               | Yes                 |
| Stack $\times$ year FE        | Yes                | Yes                  | Yes               | Yes                 |
| Adjusted $R^2$                | 0.733              | 0.710                | 0.789             | 0.678               |
| N                             | 121,955            | 249,137              | 5,483             | 28,702              |

Table A6: Accounting for multiple state-level presence

This table shows the same regressions as in Table 3, suppressing the coefficients of the control variables. In this table, we define a firm as affected by distress and non-distress driven local newspaper closures based on the state-level presence data by [Garcia and Norli \(2012\)](#), which counts states mentioned in 10-K filings. We define a firm to be affected by a newspaper closure in a given year if the firm operates in any of the U.S. states that experienced a newspaper closure in that year. We carry forward the data as of 2008 for future years. Standard errors are clustered at firm level, and given in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, or 1% level respectively.

|                           | Return volatility   | Idiosyncratic risk | Systematic risk      |
|---------------------------|---------------------|--------------------|----------------------|
|                           | (1)                 | (2)                | (3)                  |
| Post distress closure     | -0.112<br>(0.106)   | -0.036<br>(0.101)  | -0.166***<br>(0.054) |
| Post non-distress closure | -0.245**<br>(0.113) | -0.197*<br>(0.108) | -0.168***<br>(0.056) |
| Controls                  | Yes                 | Yes                | Yes                  |
| Stack $\times$ firm FE    | Yes                 | Yes                | Yes                  |
| Stack $\times$ year FE    | Yes                 | Yes                | Yes                  |
| Adjusted R2               | 0.758               | 0.757              | 0.751                |
| N                         | 255,633             | 255,633            | 255,633              |

Table A7: Distress and non-distress-driven newspaper closures and media coverage

This table reports the results of a regression of media coverage measures on a dummy variable that is set to 1 for affected firms after a distress-driven closure and to zero otherwise, on a dummy variable set to 1 for non-distress-driven closures and to zero otherwise, the natural logarithm of market capitalization, Tobin's Q, sales growth, leverage, profitability and R&D scaled by total assets as firm-level control variables, stack fixed effects interacted with firm fixed effects, and stack fixed effects interacted with year fixed effects on the sample of affected firms and for each event-year stack never-affected firms around the event year as control subjects, using Poisson pseudo-maximum likelihood regressions. The news analytics measures are based on the PR Edition, which aggregates information from global media organizations including PRNewswire, Canadian News Wire, and LSE Regulatory News Service. Standard errors are clustered at firm level, and given in parentheses. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, or 1% level respectively.

|                           | News items<br>(1)    | Relevance<br>(2)     | Novelty<br>(3)       | Pos<br>(4)           | Neg<br>(5)        |
|---------------------------|----------------------|----------------------|----------------------|----------------------|-------------------|
| Post distress closure     | -0.016<br>(0.058)    | 0.033<br>(0.046)     | 0.019<br>(0.032)     | 0.030<br>(0.048)     | 0.024<br>(0.084)  |
| Post non-distress closure | -0.105***<br>(0.040) | -0.083***<br>(0.026) | -0.059***<br>(0.019) | -0.081***<br>(0.028) | -0.053<br>(0.067) |
| Stack $\times$ firm FE    | Yes                  | Yes                  | Yes                  | Yes                  | Yes               |
| Stack $\times$ year FE    | Yes                  | Yes                  | Yes                  | Yes                  | Yes               |
| N                         | 202,080              | 201,219              | 201,219              | 201,561              | 186,439           |

Table A8: Distress and non-distress-driven newspaper closures and ZIP-level misconduct rates

This table shows the results OLS regressions of a dummy indicating whether a respective ZIP code-year observation was associated with a corporate violation or misconduct on a dummy variable that is set to 1 for a ZIP code after a newspaper closure, ZIP code fixed effects, and state  $\times$  year fixed effects in column 1, where the sample only consists of affected ZIP code. Column 2 adds control group observations to the sample consisting of ZIP codes never affected by newspaper closures around the respective closure year for every event-year stack. State  $\times$  year fixed effects are replaced by stack  $\times$  state  $\times$  year fixed effects. \*, \*\*, and \*\*\* indicate statistical significance at the 10%, 5%, or 1% level respectively.

| Sample                                | Idiosyncratic risk |                           |                           |
|---------------------------------------|--------------------|---------------------------|---------------------------|
|                                       | Affected<br>(1)    | Affected + control<br>(2) | Affected + control<br>(3) |
| Post closure                          | 0.003*<br>(0.002)  | 0.008***<br>(0.002)       |                           |
| Post distress closure                 |                    |                           | 0.004<br>(0.004)          |
| Post non-distress closure             |                    |                           | 0.009***<br>(0.002)       |
| Stack $\times$ ZIP FE                 | Yes                | Yes                       | Yes                       |
| State $\times$ year FE                | Yes                |                           |                           |
| Stack $\times$ state $\times$ year FE |                    | Yes                       | Yes                       |
| Adjusted R2                           | 0.415              | 0.410                     | 0.410                     |
| Obs                                   | 1,209,905          | 7,121,558                 | 7,121,558                 |

## A9 Narrative classification: process and examples

We hand-collect information on the reason for the newspaper closure and use a narrative classification method to separate distress-driven and non-distress-driven closures. For each newspaper closure, we search for information about the circumstances of the closure using the following sources: Factiva, newspaper archives, Wikipedia, Chronicling America, blogs, or online forums. We classify a newspaper closure as ‘distress driven’ if any of the following conditions are mentioned in any of our sources:

- Declining advertising revenues
- Declining circulation numbers
- Prior financial losses
- Prior staff cuts or threats thereof
- Failed attempts to restructure the newspaper

The following pages show examples of press articles used in the narrative classification. The first two articles cover newspaper closures that we classify as distress-driven.

Newspapers for which we do not find any evidence of distress as the main reason behind the closure are classified as ‘non-distress-driven’. Reasons for such closures include within-group consolidation, newspaper mergers that are unrelated to distress, or personal reasons. After the two examples of distress-driven closures, we present two examples of non-distress driven closures. The first relates to the reorganization of six local newspapers in the Bay Area into two — a within-group consolidation that is motivated by reader preferences. The second example is about the death of the founder and publisher of ‘The Richmond Voice’, who passed away the age of 71. For 45% of non-distress-driven closures (84 of 187), we are unable to identify the reasons behind the closure.

UNITED STATES PROJECT

## As Baltimore *City Paper* faces the reaper, stakes mount for alt-weeklies

JULY 27, 2017  
By BAYNARD WOODS



Photo by Baynard Woods



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IT WASN'T ENTIRELY SHOCKING when the Baltimore Sun Media Group announced earlier this month that it would close *City Paper*, Baltimore's 40-year-old alternative weekly, before the end of the year.

When we found out in 2014 that *The Sun* was buying *City Paper*—now, that was a shock. *City Paper* was founded, in part, to goad, mock, and compete with what we saw as a staid and often boring daily. It was what we were the “alternative” to. Worse, BSMG was owned by Tribune Publishing (now Tronc), which seemed like corporate media at its most vile.

At the time, I was *City Paper*'s senior editor. I remember the stunned looks on the faces of my colleagues as corporate executives came into our ramshackle brownstone to tell us we'd be moving, in one week, to *The Sun*'s brutalist headquarters on Calvert Street.

In the kind of language only we were fit to print, we wondered: *What the fuck?* Why did they even want *City Paper*? Was it for the racy strip club ads that a family paper couldn't print? Or was it an effort towards a print-media monopoly in the city?

“Alt weeklies...report on the cultural life of a city in a way that neither big daily papers nor websites can,” I wrote at the time, in a *New York Times* op-ed:

*Big dailies are...being squeezed to cut costs by their corporate overlords, and when they trim, their targets are typically the seemingly marginal, underground and emerging beats that alt weeklies specialize in. And while there are some great hyperlocal websites, the whole idea of the Internet—untethered to geography, universal in topic and voice—pushes against the sort of groundedness that alt weeklies provide.*

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I was worried, I wrote, “not that things will change overnight, but that over time, under corporate ownership, we will lose our edge.” *City Paper* staffers knew people at *Metro Pulse*, the Knoxville, Tennessee, weekly that was acquired by E.W. Scripps in 2007. They seemed to be doing OK.

But Scripps, which also owned the daily paper in Knoxville, killed *Metro Pulse* just months after we were bought. And while things went relatively well in Baltimore for a few years, it was hard for me then to imagine a long-term future under *The Sun*. In 2015, I quit as a full-timer. I maintained a role there as editor at large, and watched my friends continue to do more with less.

Earlier this year, *City Paper* formally filed for recognition as part of the Washington-Baltimore News Guild. Baltimore Sun Media Group recognized the union—and, in the same meeting, told the staff they were closing the paper.

<https://twitter.com/ssdance/status/883429256935727105>

I wasn't at the meeting, but staff members say it was brief and stunning. After the hatchet man left, they decided to go somewhere to get lunch. They took the elevators, which were decorated with posters featuring the *Sun*'s new post-election motto: “Journalism Matters Today More Than Ever.”

**The alternative weekly never failed to do what it was supposed to do—cover Baltimore in a muckraking way and refuse to cave to popular opinion.**

THE SAD IRONY OF THIS SLOGAN is that alt-weeklies like *City Paper* are more important than ever. Alts offer an antidote to many of the media problems that became evident during the 2016 election and the beginning of the Trump presidency.

Alt-weeklies have never had the kind of access enjoyed by dailies and TV networks; accordingly, we have never worried about losing it for asking inconvenient questions. We favor transparency over false balance or feigned objectivity. We've always been pretty sure that every flack behind a podium is

lying, and wonder why everyone else is just starting to realize that.

When the Baltimore Police Department and athletic apparel giant Under Armour—whose owner Kevin Plank is the recipient of one of the biggest tax deals in the city’s history—teamed up to redesign the notorious police station in the Western District of Baltimore, the *Sun* managed to keep a straight face. *City Paper* mocked the whole thing as a [hollow PR gambit](#), while also directly addressing the underserved, overpoliced residents of the neighborhood:

*“It seems as though the idea is that if the police had better stuff they’d stop beating people and sometimes killing people and, as a video just revealed what so many have said for decades, planting drugs on people. Better working conditions are good, but I’m not seeing how new digs fix the kind of cruelty and lawlessness that we’ve seen out of the department. What about you, the community? What kind of healing do you get?”*

“The alternative weekly never failed to do what it was supposed to do—cover Baltimore in a muckraking way and refuse to cave to popular opinion,” wrote film director and longtime Baltimore resident John Waters in a letter to the *Sun* following the announcement.

Alt-weeklies share the shortcomings of many newsrooms. For instance, too many papers—even in majority black cities like Baltimore—primarily hire white writers who too often cover white parts of town. But several have made memorable strides to address the problem. Former *Washington City Paper* arts editor Glenn Dixon credits the weekly’s former editor, late *New York Times* media columnist David Carr, with “creat[ing] a replicable model to identify and cultivate the talent of young writers of color.” Carr’s recruits included Jelani Cobb and Ta-Nehisi Coates, who told Dixon after Carr’s death that he “can’t imagine himself here right now without *City Paper*.”

“Words fail as to what a loss it would be,” says Lee Gardner about the end of alternative news sources in American cities. Gardner, currently a reporter at the *Chronicle of Higher Education*, edited the Baltimore *City Paper* for nearly a decade and also worked at *Metro Pulse*.

“Many people wouldn’t feel it at first,” says Gardner. “But over time they definitely would.”

**None of us were professional fundraisers, none of us had experience doing that. It’s a whole new idea. People are kind of used to donating money to public radio stations, public television, but to a newspaper with ads?**

**AFTER STAFF LEARNED OF** *City Paper*’s death sentence, I began working with editor Brandon Soderberg to try to figure out ways to save it before the news went public.

Knoxville seemed to offer hope. After Scripps closed the *Metro Pulse*, a few staffers started a new weekly paper, the *Knoxville Mercury*. The *Mercury* launched as a publication of the

nonprofit Knoxville History Project, but maintained its ability to sell print ads, the bread and butter of every alt-weekly.

Before we could call him to ask for details about the model, editor Coury Turczyn announced that the *Mercury* would cease publication.

“Originally, we thought we’d be able to regain the same levels of advertising revenue that *Metro Pulse* had enjoyed before it was closed,” Turczyn wrote on July 5. “That alone would’ve covered all of our expenses to publish the paper with our micro-sized staff. But by the time we were able to launch *The Mercury* some six months later, the market had moved on.”

Turczyn spoke with me about the paper’s model by phone on July 19, the day the final issue of the *Mercury* hit the streets.

“Unfortunately, none of us were professional fundraisers, none of us had experience doing that,” he said of the nonprofit aspect of the business. “It’s a whole new idea. People are kind of used to donating money to public radio stations, public television, but to a newspaper with ads? That’s a whole different idea.”

**OTHER, MORE ESTABLISHED PAPERS** are also experimenting with the nonprofit model to fund individual stories and projects—and not just for a single outlet. Chris Faraone, editor of DigBoston, founded the Boston Institute for Nonprofit Journalism (BINJ), which is a [possible](#) template that other cities, like Baltimore, could follow.

“It’s still early on,” says Jason Zaragoza, head of AAN, which is contemplating acting as a fiscal sponsor for alt-weeklies that want to incorporate a model like BINJ. “Some papers can make it work,” says Zaragoza about such a model, “but I think it works, at least right now, as a supplement for the main business.”

It seems clear to everyone involved that we need to do something—or a lot of different things—so we can find out what works. *The Stranger*, Seattle’s Pulitzer-winning alt-weekly, recently announced glossy covers, longer stories, and a reduced production schedule, for instance.

The recent news from Baltimore and Knoxville should remind all weeklies just how high the stakes are. But if the imminent death of *City Paper* spells the death of corporate alts, Turczyn makes it clear that the *Mercury*’s fate does not spell doom for a similar model in other markets.

“I think our business model was ultimately too complicated to explain to potential donors,” he wrote in an email, “but that doesn’t mean somebody else can’t still figure it out.”

## Cincinnati Post stops the press after 126 years

The Cincinnati Post, known for colorful, lively journalism and launching numerous employees to successful careers, went to press Monday for the last time.



— "It's a sad day, but we're going out with heads high. This paper made a difference in the community," said Mike Philipps, the editor of the Cincinnati Post, in the newspaper's final edition. David Kohl / AP

Dec. 31, 2007, 6:14 PM GMT+1 / Source: The Associated Press

The Post newspapers printed their final editions Monday, ending a 126-year run. However, the final editions also carried some news – their parent company will keep a remnant alive in the form of a Kentucky-oriented online site.

"-30-", a symbol traditionally used by journalists, printers and telegraphers to signal the end of a dispatch, proclaimed the front-page headline in the last Cincinnati and Kentucky newspaper editions.

In a front page story about the closing, editor Mike Philipps said: "It's a sad day, but we're going out with heads high. This paper made a difference in the community."

The Post and its sister Kentucky Post edition have been struggling for decades, part of a national decline in afternoon newspapers and of multiple daily newspapers in U.S. cities. E.W. Scripps Co., based in Cincinnati, decided in July to close The Post newspapers when a joint operating agreement with Gannett Co. expired at the end of 2007.

In a story in Monday's editions headlined "Web site to carry on Post tradition," The Post reported that the Scripps company will keep a Kentucky presence with kypost.com. The site beginning Tuesday will supersede the current Post site and will share content with the Scripps-owned Cincinnati TV station WCPO-TV and its Web site.

One Post staffer, Kerry Duke, will stay on as the site's managing editor. The site will also use a full-time reporter, freelance journalists and contributions from "citizen journalists" in addition to WCPO and news services. The site will focus on the three counties just across the Ohio River, the northern Kentucky area where the majority of The Post newspapers' last subscribers have been.

### 'It's sad but inevitable'

The site expects to be sustained by advertising, particularly ads targeted to what it calls "life in the 859," the northern Kentucky telephone area code.

"It's a low-cost approach, but if you want to maintain the presence, it's probably the only alternative," said John Morton, an independent newspaper industry analyst based in Silver Spring, Md. "It's better than going out completely, and clearly there is opportunity there."

Rich Boehne, Scripps' chief operating officer, said Scripps hopes to gradually build the kypost.com site.

"It's been an incredible brand in northern Kentucky," he said.

Boehne was among dozens of newspaper executives and retirees who gathered to watch the last editions roll off at The Cincinnati Enquirer's printing center.

"It's sad but inevitable," said William R. Burleigh, Scripps' chairman and former Post editor. "There's a lot of history, a lot of wonderful people."

Philipps, a 30-year veteran of the newspaper, said the final editions Monday were focusing on the newspaper itself as a keepsake. Some 9,000 extra copies were printed beyond the paper's weekday circulation of about 27,000. The editions included stories about The Post's history, remembrances from staffers and readers, archival photos such as actor Cary Grant's 1955 visit to The Post newsroom, and farewell columns.

"We're going to make ourselves count right to the end," he said earlier. The staff must then turn to myriad tasks of shutting down, such as cleaning out drawers, turning in laptops and keys, processing paperwork and turning off phones.

The Post was known for colorful, lively journalism, investigations and crusades against political cronyism and for civic reforms, and for launching numerous employees to successful careers in journalism, communications and education.

Originally called The Penny Paper when it was started in 1881, the paper was renamed The Penny Post by E.W. Scripps, who assumed control in 1883. The newspaper became The Cincinnati Post in 1890, when its Kentucky Post edition began.

#### **Down to 50 staffers**

The Post newsroom was down to about 50 people at the end, and its daily circulation was less than a tenth of the 270,000-plus it enjoyed in 1960, before changing lifestyles, the expansion of television news, and later, the rise of multimedia news and advertising sources, sapped readership. Cleveland and Columbus, Ohio's two largest cities, lost an afternoon paper each decades ago.

Joint operating agreements under the Newspaper Preservation Act of 1970 allow newspapers to merge business operations when one is facing financial failure. Gannett, which owns The Cincinnati Enquirer where the Post had been printed for about three decades, notified The Post three years ago it would not renew their agreement when it ended.

Scripps plans in June to split its businesses into two companies. A new company called Scripps Networks Interactive will take national cable networks such as the Food Network and HGTV and online shopping businesses, while the E.W. Scripps company focuses on newspapers and broadcast TV stations. Boehne, the one-time Post reporter who will head the restructured Scripps company, said it will maintain a strong local news presence with WCPO-TV, wcpo.com, and the kypost site.

Many readers and officials in Cincinnati and the nearby northern Kentucky communities The Post served have lamented its passing.

"A piece of history has gone. Obviously a voice has gone," said Alicia Reece, an Ohio tourism official and former Post intern who served on the Cincinnati City Council. "On the other hand, they were a foundation for a lot of writers and other people who moved into higher positions. So the legacy lives on."



SAN FRANCISCO (AP) - Six daily newspapers in the San Francisco Bay Area will be consolidated into two, one serving Oakland and the East Bay and the other Silicon Valley, the Bay Area News Group announced Tuesday.

In the East Bay, The Contra Costa Times, Oakland Tribune, The Daily Review and The Argus will become the new East Bay Times. In Silicon Valley, the San Jose Mercury News - the group's flagship publication - and the San Mateo County Times will become the Mercury News, said BANG's vice president for audience Dan Smith.

Subscribers in Oakland, Hayward and Fremont also will receive new community weeklies, Smith said.

Smith said the changes, starting April 5, were prompted by an extensive survey of subscribers.

"Our East Bay readers wanted more news about the East Bay and less news about Silicon Valley so, by focusing on two regional brands instead of a large group of newspapers trying to serve the Bay Area, we'll better achieve our mission," he said.

There will be a modest reduction in staffing, Smith said, adding that most would be connected to the newspapers production and a small number to the newsroom.

"All of our decisions are being guided by research," he said.

With the changes, the group aims to bolster regional news reporting in the East Bay, adding coverage of transportation, the environment and local business by placing new reporting and editing resources in its community news bureaus.

The news organization will also combine two of its websites - [contracostatimes.com](http://contracostatimes.com) and [insidebayarea.com](http://insidebayarea.com) - into an East Bay-focused site, [eastbaytimes.com](http://eastbaytimes.com).

BANG also publishes the Santa Cruz Sentinel, the Marin Independent Journal, The Reporter in Vacaville and the Times-Herald in Vallejo.

The group has a daily combined circulation for print and digital subscribers of just under 400,000 on weekdays and 525,000 on Sundays.

Washington Examiner

Washington Examiner

## Jack Green, The Voice founder and publisher, dies

By Washington Examiner  
June 26, 2014 5:10 pm

RICHMOND, Va. (AP) — Jack J. Green, founder and publisher of two community newspapers in Richmond and Hampton Roads, has died. He was 71.

The Voice says on its website that Green died Thursday from a chronic lung-related illness.

Green founded The Voice in 1985 to serve the black community. The weekly newspaper later became The Richmond Voice, followed by a sister publication, The Hampton Roads Voice.

Green also was a member of the Nottoway County Board of Supervisors, and past president of the Nottoway County Branch NAACP. He also was a past president of District IV Community Action Program in Hampton.

Green was a U.S. Air Force veteran who served in Vietnam.

Funeral arrangements are pending.

Online:

The Voice: [voicenewspaper.com](http://voicenewspaper.com)