Labor Threats, Product Market Competition and Strategic Disclosures[1]

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Abstract

I investigate the nature of strategic disclosure by managers facing labor related threats and product market competition from existing rivals. I test and find empirical support for extant theory that when a firm faces labor related threats and product market competition simultaneously, the additive forces of non-disclosure of good news weakens. In the face of competition and labor threats, the weakened incentive to hide good news may seem counterintuitive, but it helps managers to curtail aggressive bargaining by its employee base. I further contribute to literature by introducing three new measures of labor related threats. Using these new measures, I document that firms withhold good news when facing either labor threats or product market competition individually. But the joint presence of both entities weakens the incentives of firms to withhold good news, rather than strengthening it.

Keywords: Product Market Competition, Voluntary Disclosure, Union, Self-Sabotage

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1. Introduction

A rich body of literature examines the disclosure choices made by firms that face threats from organized labor unions. Managers of unionized firms operate under countervailing forces of capital market expectations of profitable performance, and pursuit of rent extraction by organized labor unions. While shareholders value profitable performance, labor unions bargain aggressively to extract a greater share from the profits for the employees of the firm that are covered by collective bargaining agreements[2]. Capital markets impound the threat of abnormal rent extraction by aggressive labor unions and value firms net of such transfers. Hence, managers have the incentive to minimize expected rent transfers to firms' employees, thereby keeping a larger portion of the profit pie for firm's shareholders. This apparent tension between the concerns of employees and the concerns of shareholders induces managers to withhold information or avoid projecting an overtly positive outlook. Prior literature documents managers of unionized firms making a variety of accounting choices that seek to steepen information asymmetry and signal a negative outlook for the firm to curtail assertive bargaining by its labor union[3].

Labor unions face bargaining costs[4] that prevent them from bargaining unless benefits of bargaining exceed costs of bargaining. Bad news disclosure tends to have adverse capital market consequences for the firm, but then unions also back off from bargaining as there might be little that can be extracted when firm is not performing well. The benefits from bargaining

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[2] Christofides and Oswald (1992), Blanchflower et al. (1996) document that labor unions can extract higher wages from profitable firms. Hirsch (2008) documents that unionized employees can extract 'above market' rents from firms owing to higher leverage they gain during negotiations from collective bargaining agreements.

[3] See Hilary (2006), Bova (2013), Chung et al. (2016), Hamm (2018), Chang et al. (2022) for details of how firms reduce disclosure, miss analyst benchmarks, are more likely to provide bad news disclosures than good news disclosures, smoothen earnings and manage earnings by manipulating accruals and real earnings respectively.

[4] Bargaining costs include litigation, arbitration costs, costs incurred to organize strikes, protests, picketing etc.

do not compensate for the costs associated with bargaining. This makes disclosures a delicate balancing act for managers. On one hand, she knows that bad news disclosure would make the union or employee base curtail their aggressiveness but can have negative impact on firm valuations. On the other hand, good news disclosures signaling profitability would have healthy valuation outcomes for the firm but also invite aggressive bargaining by unions. Since bargaining by unions is likely obtained when a certain threshold of profitability is met and expected benefits from bargaining in the form of increased wages, bonuses, facilities etc. exceed costs of bargaining[5], manager tends to withhold good news or disclose bad news.

Product market competition also plays a significant role in driving managerial disclosure behaviour. Companies operating in industries characterized by a high competition face the potential appropriation of profits by existing rivals. Good news disclosures signalling future profitability from a firm's manager in such an industry reveals information that may lead rivals to take actions detrimental to disclosing firm's profit. Extant literature assigns the nomenclature of *proprietary costs* to the disadvantages faced by firms from good news disclosures. For example, proprietary costs are assumed to be high when a firm is operating in a highly competitive industry (oligopolistic or otherwise) or in an industry where technological innovation is rapid (proxied by high R&D expenses, patent filings etc.). If favourable disclosure by one firm helps in production and pricing decision of the other, thereby appropriating some of the profits of the former, then such a disclosure is sub-optimal. Managers can choose not to project positive prospect (even avoid disclosures completely) in such a scenario as action by rivals can impose costs on the incumbent in form of loss of profits[6].

The disclosure choices made by firms in presence of such multiple recipients (capital markets and competition, or capital markets and labor union etc.) have been studied extensively. In each

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[5] See Arya and Ramanan (2022)

[6] See Wagenhofer (1990) for detailed model on firm's disclosure strategy when facing opponent.

of these scenarios the firm faces conflicting disclosure incentives- it wants to disclose good news to one recipient (capital market) but withhold good news from the other (rival or union). What would be the disclosure choice of a firm that faces two recipients at the same time with whom disclosure incentives are aligned individually? That is, what would the firm disclose (or not disclose) when it faces off with a labor union and a product market competitor simultaneously, when, if faced individually, the firm would withhold good news in each case?

Intuition dictates that firms should double down on withholding good news in such cases as withholding good news and disclosing bad news (if available) takes care of both proprietary costs concerns and prevents extractive bargaining by labor union. Arya and Ramana (2024), *AR24* henceforth, challenge this prevalent thinking and analytically examine the disclosure choices when firm faces recipients that impose identical disclosure incentives. For example, a firm facing entry threat or rival and labor union, or a firm facing political costs or regulatory threat and a rival etc. *AR24* shows that when a firm must deal with the joint presence of such entities that impose aligned disclosure incentives, economic forces that lead to withholding of good news is not additive. Instead, the incentive to *withhold* good news weakens.

The intuition behind *AR24* is that a firm's disclosure has a direct impact on union's actions and an indirect impact on union's action through the actions of the firm's product market competitor who is also observing the same disclosure. When the firm faces each of them individually, it discloses unfavourable news, in line with prediction of existing literature. The joint presence of competitive and labor threat weakens firm's incentive to project a negative outlook. This disclosure seems to be counter- intuitive because indication of better prospects can induce both- aggressive bargaining by the union (employee base) as well as strategic action by the product market rival. But what may not be immediately apparent is that the rival's actions eat into the profits of the disclosing firm, leading to a decrease of the overall profit pie for the firm. However, the smaller pie leaves less profits from which the union can bargain for its share.

Thus, labor union's decision to bargain hard or not is directly impacted by disclosure of favourable news (or less unfavourable news) and indirectly impacted by the actions of the product market rival. *AR24* goes on to make the argument that their model is applicable in a broader setting where the firm's disclosures are in a certain direction when it faces each recipient individually, but joint presence of both the recipients induces the firm to make the firm to disclose in the opposite direction.

I test the prediction of *AR24* in a setting where a firm faces labor related threats and product market competition at the same time. I test whether in the face of product market competition and labor related threats, managers strategically disclosing good news rather than bad news to reduce rent extraction by labor force is the equilibrium outcome. Managers choose to be exposed on one front to reduce bargaining leverage of labor force. This strategic 'playing off' of two opponents- employees and rivals, through good news disclosures leads to availability of more value to be transferred to shareholders of the firm.

I expand the ambit of threats arising out of unionization[7] to include a broader spectrum of threats arising out of labor related issues as perceived by managers and external observers. While threats arising from organized labor are a significant subset and have been a matter of examination of previous research, other labor related issues like strikes, hiring, layoffs, resignations, union pacts, workforce-salary etc. can also mold a firm's voluntary disclosures. Further, unionization tends to be persistent and extant studies that use unionization measures (usually a binary variable) lack the power to test labor threats that are sporadic, and/or of pressing nature. To that end I introduce three novel measures that proxy for labor related threats at a more granular level. The first two measures are based on textual analytics of discussion of labor related issues in quarterly earnings conference calls and the last one is based on text

[7] Current state of accounting literature at the intersection of labor and firm disclosures revolves around measures of unionization, collective bargaining proxies, etc. as one of the main independent variables.

analysis of sentiment of labor related news. The first one measures imminent, pressing threats faced by a firm from labor force, and the second one borrows tools from computational linguistics and computes a continuous ongoing measure of labor related threats faced by a firm. The first and second measures give us an understanding of how managers themselves perceive labor risks and threats while disseminating information during quarterly earnings conference calls. The third measure of labor related threats closes the loop by examining how external observers (sentiment of labor news) are looking at labor related issues faced by a firm. These three new measures along with a fourth one- an extant measure of labor related threat[8] gives us a holistic picture of labor threats faced by firms. I use the first text-based measure (a binary measure of existence or absence pressing labor related threats) in main test and use the rest of the three as robustness check.

The rest of the article is organized as follows- Section 2 proceeds with literature review and development of hypothesis, Section 3 provides details of sample, key variables creation, controls and descriptive statistics. Section 4 presents our empirical methodology and results of our hypothesis, Section 5 has robustness checks, and Section 6 concludes the paper.

2. Prior Literature and Hypothesis Development

An extensive body of work in analytical literature demonstrates that firms are dissuaded from disclosing a positive outlook due to costs imposed by heightened competition. Good news disclosures by informed firms induces overproduction by uninformed firms. On the other hand, bad news disclosures curtail production. Thus, managers of firms with private information on future state of demand have the incentive to withhold good news and disclose bad news about future state of demand. Verrechhia (1983) models such disclosure choices in a competitive environment under proprietary cost considerations. He argues that increased competition leads

[8] We also test the prediction of AR using extant firm-year measure of unionization (Hamm, 2018) as a robustness check.

to less disclosures owing to proprietary cost concerns. On the other hand, competitive pressures defined in terms of entry costs induce voluntary disclosures [Wagenhofer (1990)]; Darrough and Stoughton (1990)[9]]. Investors impound the potential negative impact on a firm revealing proprietary information and desist from imposing adverse selection on such firms. In a post entry duopoly game, Clint and Verrechhia (1997) argue that firms with information about very high (very low) state of the world hide it from uninformed competitors. In equilibrium, a higher level of competition discourages disclosure. Li (2010) empirically tests predictions of Clint and Verrechhia (1997) and finds that existing competition decreases disclosure quantity and quality. She also finds that existing competition degrades disclosure quantity but enhances quality through tempering optimism in profit forecasts and reducing pessimism in investment forecasts. Huang et al. (2017) lend further credence to proprietary cost hypothesis by demonstrating that tariff reductions increase competition and reduce management forecasts.

Extant research pertaining to the impact of product market competition on accounting choices provides a mixed menu of results. On the one hand, Marciukytyte and Park (2009), Wang and Winton (2012), Datta and Datta (2013), and Markarian and Santalo (2014) provide evidence that competition moderates accruals management and increases informativeness of earnings. On the other hand, studies by Balakrishnan and Cohen (2013), Cheng et al. (2013) and Karuna et al. (2017) demonstrate a negative association between competition and earnings management, possibly alluding to *'race to bottom'* explanation according to which firms in competitive markets make inappropriate accounting choices to present a rosier picture.

A large body of literature documents that labor unions can extract above- market rents from firms and hence, managers of unionized firms have the incentive to signal a negative outlook to reduce such extraction. Managers do so by manipulating the expectations of analysts or by

[9] Verrechhia (1983) puts forward *proprietary cost theory*. Darrough and Stoughton (1990) and Wagenhofer (1990) put forward *entry deterrence theory.*

manipulating earnings, or a combination of both (Bova, 2013). Drawing from the model outlined by Fischer and Verrecchia (2000), Bova (2013) shows that managers may bias profitability signals either way, depending on the trade-off between benefits of missing analysts' expectations and costs associated with missing expectations. He documents that unionized firms miss earnings estimates and manipulate accruals around bargaining events with labor unions. Further, Chung et al. (2016) finds evidence of managers of unionized firms holding back good news around contract negotiations with unions. Aobdia and Cheng (2018) find that non-unionized firms put unionized peers under pressure prior to contract negotiations by releasing more information, particularly information that can be construed as 'good news'.

Prior to this set of empirical papers, a strand of literature touched upon superior leverage enjoyed by organized labor unions. Blanchflower et al. (1996) find that the amount of rent unions can extract is an increasing function of firm's profitability. Hirsch (1991, 2008) document the ability of organized labor unions to extract above market rents owing to better bargaining power they enjoy during contract negotiations. Another strand of literature reveals unionized firms engaging in income smoothing and accruals manipulation (Hamm, 2018), real earnings management (Chang et al., 2022) and tone management in earnings press releases (Ayaydin et al., 2018) to shelter firm's earnings from extractive labor unions. Performance understatement by managers in presence of labor unions finds further support in Baldwin (1983) and Grout (1984). Managers further seek to shelter firm's resources from them by holding less cash (Klasa et al. 2009), holding more debt (Bronars and Deere 1991) and by decreasing frequency of good news disclosures (Chung et al 2016).

The literature on disclosure choices made by unionized firms and firms facing product market competition laid out so far is unidirectional in the sense that they largely document unionized firms and firms facing competition taking actions that signal a negative outlook to prevent value transfer from shareholders to employees or to deter product market competitor from taking actions. This indeed is within the predictions offered by the analytical models in which firm must manage two countervailing forces with conflicting incentives- capital markets and an opponent who could be an existing rival, potential entrant *or* capital markets and a labor union. The equilibrium disclosure decision taken by the firm impounds the incentives of both capital markets and actions by an existing competitor or labor union. The literature is, however, silent on the type of disclosures made by a firm that faces union demands or other labor related threats *as well as* threats from a product market rival. I contribute to the literature by testing prediction of *AR24* by examining the direction of disclosures a firm faces intense competition as well as extant threats from its employee base[10] by introducing new measures of labor threats.

I present the intuition behind the result of *AR24* as follows. Consider firm F, its product market rival R, and its labor union L. Firm F gets a private signal about the future demand a with some probability p. Once the firm is informed of this signal, it can either truthfully disclose a (whether good or bad) or keep quiet as disclosure is subject to audit. Thus, firm F's disclosure is $d \in \{a, \emptyset\}$, where $\emptyset$ denotes that firm has chosen not to disclose what it has observed (non-disclosure). Figure 1 below shows the timeline of the game.

[Figure 1 here]

The labor union L observes the disclosure (good news or bad news or non-disclosure) and chooses its bargaining intensity t. Bargaining is costly and hence union's utility function is quasi-linear; linear, increasing in firm's profits, and quadratic, decreasing in bargaining intensity. So, a union must decide if it is beneficial at all to bargain hard based on what the firm discloses. Finally, consider the actions of the product market rival R. Based on the disclosure d firm R chooses whether to take strategic action or not. The decisions of the labor union and

[10] Employee base can be unionized or ununionized. For the sake of exposition of mechanism in this section of the article, we consider a firm facing organized labor union as an example.

product market rival are simultaneous. Along the game, actual demand a is realized and each player get their share of profits. The manager of the firm must decide on the disclosure d early in the game such that firm value is maximized when profits are realized at a later stage. She must consider how the rival and union would behave based on her disclosure. *AR24* show that union's bargaining is increasing in value of disclosure (good news) and decreasing in intensity of competition. So, it is in the interest of the firm to disclose if it has good news, rather than withhold good news. Good news would entice the rival to act, thereby disciplining the union indirectly from bargaining too aggressively. *AR24* shows that the manager is more likely to disclose good news. Good news disclosure induces the rival to make pricing and quantity decisions that reduce disclosing firm's profits. This reduction in profits weakens labor union's bargaining position and they desist from bargaining hard. If either of the threats are weak, firms continue to withhold good news as usual- either to deter rival action or keep labor force at bay.

This brings the discussion to the testable hypothesis-

A firm withholds good news when faced with a rival and labor threat individually, but in their joint presence the firm is unlikely to withhold good news.

To the best of my knowledge, I am first to empirically test a setting predicted by *AR24*. To that end I contribute to the strand of literature that examines voluntary disclosures in face of multiple audiences. My second contribution lies in introducing two entirely new measures to proxy labor-related threats faced by a firm. Existing continuous measures based on industry unionization rates assume labor's bargaining strength even if a firm has no union that bargains collectively on behalf of its employees (Hilary 2006). Existing binary measures of unionization fail to account for persistence of unionization among unionized firms and introduce lack of firm- level heterogeneity (Hamm 2018). The measures that I introduce are based on text analytics of earnings calls and news articles abstracts away from presence of union and proxy for labor threats faced by a firm in general. They also introduce time varying heterogeneity in labor related threats faced by a firm emphasizing that a unionized firm may not always be facing labor threats, and a non-unionized firm may be facing labor threats arising out of other issues[11].

3. Sample Construction, Key Variables and Descriptive Statistics

Sample Construction

To test the prediction of *AR24* I use a sample of US firms from 2008-2019. The data comes from the intersection of quarterly Compustat, Hoberg and Philips product- market fluidity dataset and management capex forecasts from I/B/E/S. I remove financial firms, firms with negative book values, penny stocks (stock price <$1), and firms whose financial year and calendar years do not converge in December. Also, I consider annual capital expenditure forecasts and keep the earliest quarterly forecast from IBES estimates.

[Table 1 here]

All continuous variables are winsorized at the top and bottom one percentile, and I allow for a full set of available controls. The final sample has 33142 observations across 1288 firms. Table 1 provides a brief description of our sample construction.

A. New Measures of Labor Related Threats

Existing measures of unionization, a key aspect of labour relations, often rely on industry unionization rates (Hilary, 2006) or simple binary indicators of union presence (Hamm, 2018). However, these measures fail to capture the nuanced and dynamic nature of labour threats faced by individual firms. For one, unionization and non-unionization tend to be persistent. That is,

[11] We also test the predictions of *AR24* using unionization measure proposed by Hamm et al. 2018 as a robustness check.

a unionized firm does not get un-unionized easily, and an un-unionized firm does not get unionized easily. Furthermore, a firm may be unionized but not necessarily facing significant labour-related challenges, or conversely, a non-unionized firm may encounter substantial labour issues. Simple binary measure of unionization or an industry unionization rate based measure does not capture such subtlety.

To address this gap, I propose three novel measures to quantify the threat a firm faces from labour-related issues. The first measure utilizes text data from earnings conference calls, capturing the qualitative aspects of labour discussions pertaining to strikes, layoffs/hirings and union negotiations. I use this in the main test. The second measure employs a TF-IDF based approach to compute the proportion of an earnings conference call devoted to labor related topics. And the third measure leverages sentiments of labour-related news events like hiring/layoffs, strikes, workforce salary, union pacts, resignations etc. related to a firm. Finally, I use an extant measure of firm level unionization to test the predictions of *AR24.* Through these measures, my aim is to provide a more nuanced understanding of the labour issues related threats faced by firms. I begin with discussing the lacunae of earlier measures and explain how our measures seek to address them.

The first attempt at arriving at a firm specific measure of unionization or labor related threats involved multiplying the industry unionization rate (available from Bureau of Labor Statistics) with labor intensity, which is the ratio of the number of employees to total assets of a firm (Hilary, 2006). The measure so created is proxy for strength of labor and is agnostic to whether a firm is unionized or not. The assumption is that firms from the same industry would be under comparable pressure from unions, and any industry wide impact would be firm specific.

The next measure proposed by Hamm et al. (2018) requires textual analysis of a firm's business description (item 1) and risk factor disclosures (item 1A) from 10Ks to come up with a set of keywords related to unionization of a firm. The measure is binary, in which the presence of a related keyword(s) or phrase(s) in a firm's 10K implies that firm is unionized. This is a more generic measure and addresses the concern of the previous measure created by Hilary (2006) that validity of an industry specific measure weakens if a firm is not unionized.

Hamm et al., (2018) report that there could be divergence between firm specific union membership and industry unionization rate (p. 1207) computed by Hilary (2006). Although Hamm et al., provide a more generic and 'cleaner' firm specific version of unionization (a binary variable that takes the value 1 if firm is unionized in a given year, 0 otherwise), I find that firm unionization & non- unionization is highly persistent. The number of firms that are unionized in Hamm's sample is 20%, and many of these firms show no heterogeneity in unionization across time, that is, they stay unionized all throughout the sample (example, General Motors).

On analysing a sample of 10,924 Compustat firms between 2008-2019 (Figure 1), I find that 8,909 firms stay non- unionized throughout, and 2,085 firms (19%) stay unionized for at least one year during the sample period. This unionization rate is close to the 20% reported by Hamm et al., for their sample from 1996-2014.

As evident from the Figure 2, even among firms that are unionized, 31% (646 out of 2085) stay continuously unionized for more than 6 years or more out of the 12 years in the sample, i.e. a value of 1 for the variable *UNION_DUMMY* for these firms for more than half of the sample period, 0 otherwise. This persistence leads to a sample where there is a heavily lopsided clustering of the *UNION_DUMMY* variable[12]. Any research question that needs to exploit

[12] For example, firms like General Motors, American Axle etc. have *UNION_DUMMY=1* for all years in the sample.

heterogeneity in labor related issues at a more granular level, say quarterly, would have to make use of mis-specified regression, as unionization measure is at the year level.

[Figure 2 here]

Secondly, as within firm heterogeneity[13] is not substantial for a considerable number of firms in the sample, regression results are prone to misinterpretation. Finally, the use of labor strength or firm specific unionization does not inform us of labor related issues faced by firm as perceived by managers and external observers, that are likely to be more pressing or/and spread out over time.

I seek to address the above concerns and propose three new measures that quantifies imminent labor threats faced by firms as perceived by managers arising out of labor related issues and labor threats facing a firm as observed in news media by external entities. To reiterate, the first measure is based on text analytics of quarterly earnings calls, and it is a binary measure created using a Bag of Words (BOW) approach of keyword matching. The second measure is again created from earnings call transcripts, using machine learnings based computational linguistic technique. The third and final measure is based on sentiments of news events pertaining to myriad labor related issues.

Quarterly Earnings Conference Calls (ECC) Based Measure

A. Binary Measure of Labor Related Threat using Bag-of-Words Approach

Earnings calls following earnings press releases are important information events in capital markets [Frankel et al. 1999, Bowen et al. 2002, Bushee et al. 2003, Kimbrough 2005]. Extant literature [Matsumoto et al., 2011] documents that earnings conference calls are incrementally more informative than the accompanying earnings press release primarily because of the

[13] In Appendix D, we show results from OLS with firm-year fixed effects instead of industry-year fixed effects using Hamm's measure and our two new measures.

manager's presentation that aids in more voluntary disclosure, and presence of analysts who uncover more information through questions, which managers provide answers to. I leverage this quality of earnings conference call to create unique measure of threats arising out of labour related issues.

I examine the occurrence of strikes, layoffs, and labour union related discussions in earnings conference calls to arrive at binary measure of labour issue related threat. In any given quarter a firm might talk about any one of these threats, none of these threats or a combination of these threats. On a continuum of threat perception from no discussion of any labour related threat to discussing all three in a conference call, I say that a firm is facing an *'imminent'* labor threat from labour related issues if it discusses all the above three topics in its quarterly earnings conference call. This new measure proxies for those labor related threats that managers perceive to be strong, pressing in nature, and perhaps cannot ignore anymore.

A manager can discuss about strikes, layoff and union related issues either voluntarily or as a response to questions of analysts. The measures created do not distinguish between the two. Any discussion of these topics can be an outcome to either ongoing issues the firm might be facing or potential issues that firm might face. Whether voluntary or involuntary, discussion of these issues indicates that either the manager is concerned about threats arising from strikes, layoffs and union negotiations, or the analysts consider such issues to be pertinent and are seeking the response of managers. For example, strikes can lead to work stoppages and can trigger pushback from unions. Strikes at a firm's supplier or at a peer firm can also be a matter of concern for the firm as there could be impact from any spillover and firm's profits might be affected. Similarly, layoffs, whether firm specific or due to economy wide factors, can trigger labor unrest and they can ask for firms to reconsider its decisions that might impact the bottom line. And finally, labor union negotiations usually involve unions asking for better wages, benefits and working conditions that has the potential to whittle away much of firm's profits.

The presence of any one threat may or may not represent a very pressing concern, but the presence of all of these in a single conference call is likely an outlier event and manager can no longer ignore it, nor the analysts would allow the managers to hand wave over the issue.

To arrive at the measures, I do a Google search of earnings conference calls for unionized as well as non-unionized firms in our sample and read them to come up with a set of keywords and phrases pertaining to strikes, layoffs and union related issues[14]. Following manual reading of a random set of earnings conference calls, I create a set of keywords and phrases for strike, layoff, and union related labour issues. Table 2 below provides a comprehensive list of keywords and phrases that we come up with along with acronyms of labor unions.

[Table 2 here]

The earnings conference call transcripts are sourced from Capital IQ and programmatically checked under three headings- strike, layoff and union keywords and phrases occur in the transcript or not. If yes, it is coded as 1, else 0 for each heading. For example, if the words "strike", "right size" and "collective bargaining" occurs in the transcript, then all the three columns- strike, layoff and union take the value 1. If any one or two occur, then those columns take the value 1 and the third one stays 0. 66,510 quarterly earnings conference call transcripts of 2,438 firms[15] are programmatically parsed in this way.

In the second step I take the subset of observations in which threat from strike and threat from layoff is still 0. For those observations in which threat from strike is 0 the files are parsed again

[14] A sample Google search phrase looks like "*Ford* Earnings Conference Call Strike", "*General Motors* Earnings Conference Call Layoff", "*American Airlines* Earnings Conference Call Labor Union" etc. We read earnings conference calls transcripts of 10 unique firms each for strike, layoff, and union related keywords. Overall, we read 30 earnings conference call transcripts.

[15] A random search of 20 transcripts with the word "strike" in them did not throw up any instance of homonyms like "It does not *strike* me to be on the lower side…". Although we do not completely rule out the existence of such homonyms in at least some transcripts.

to see if any of the labor union acronyms[16] or the words "loss from", "negative" or "loss" occur in the same sentence or not. If they do, strike threat is recoded to 1 from 0, for these observations. For those observations in which threat from layoffs is 0 I parse the files again to see if the words "fire", "fires", "firing" occurs in the same sentence with "employees" or "work- force"," workforce". If they do, threat from layoffs is recoded to 1 from 0. Table 3 provides a descriptive statistic of the measures created.

Table 3 shows that 10%, 9% and 6% of the firm quarter observations are those in which firms face some kind of strike, layoff, or union related threats. This corresponds to 1696, 1677 and 1279 unique firms out of 2438 firms that face strike, layoff, or union threat in some quarter or the other respectively. 286 firms face all the above threats (*IMMINENT)* in some quarter or the other. This implies that labor related threats are more spread out across firms and time than simple firm level unionization would suggest.

Distribution of each type of threat over a larger set of firms and quarters addresses concern discussed earlier about persistence of unionization and inability to analyse impact of labor related threats that are sporadic and sudden in nature[17].

[Table 3 here]

B. Measure of Existing Competition

I lean on extant literature for our measure of existing competition. For existing competition, I use product market fluidity measure created by Hoberg et al. (2013)[18]. The top quartile of product market fluidity is coded as *HICOMP*=1, 0 otherwise, to proxy for strong and weak

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[16] These acronyms stand for the labor unions that are active in the US. For example, UAW stands for United Auto Workers. We also ensure that all acronyms, keywords, and phrases under each heading is searched for in a case agnostic way to adjust for any errors of transcription.

[17] We implement the same algorithm as above on management presentation and analyst's question and answer section separately and run our main tests (Appendix C). This allows us to cleanly identify whether managers are themselves strategically disclosing labor threats, or at the behest of analysts' questions.

[18] The measure is available from their website, https://hobergphillips.tuck.dartmouth.edu/ .

competitive threats respectively. Hoberg et al. analyze the product description of 10Ks, and their measure of competitive threat focuses on the activities of the rivals by directly measuring "*…the change in a firm's product space due to moves made by competitors in the firm's product markets.*" This ex-ante measure of competition highlights the ongoing product market threat faced by a firm. Hoberg et al. (2014) define product market fluidity as-

$$PMF = N_{i,t} \cdot \frac{D_{t-1,t}}{||D_{t-1,t}||}$$

Where $N_{i,t}$ is the firm's own normalized word vector and the normalized $D_{t-1,t}$ is the overall change in use of words from previous year. Product market fluidity, as defined by Hoberg et al. (2014), captures the annual change in a firm's product space by analysing the language used to describe its products in the 10-K report[19]. This measure compares the firm's product space with that of other firms, indicating the extent of overlap and, consequently, the level of competition. Fluidity lies between [0,1] and is multiplied by 100 for convenience. A higher overlap (higher *PMF* score) suggests increased competitive threats. Importantly, since product market fluidity relies on 10-K reports, which are mandated to be current and updated, it provides forward-looking information that extends beyond historical accounting data[20]. In my tests I split the *PMF* variable at its tops quartile to create a binary variable *HICOMP* that takes the value of 1 if *PMF* is in the top quartile of the sample, 0 otherwise.

C. Measure of Good News

Good news is proxied using a binary variable *PSURP* (short for positive surprise), that takes the value 1 if management's capital expenditure (capex, henceforth) forecast exceeds analysts' consensus, 0 otherwise. Since I test for likelihood of positive surprise, I also consider firms that

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[19] We assume that a firm's existing product market does not undergo any significant changes in a quarter.
[20] Existing measures that are inaccurate proxies for product market competition like Herfindahl-Hirschmann Index (HHI), Four Firm Concentration ratios etc. use sales data.

do not disclose, and code *PSURP* to be 0 for non-disclosing firms. If the manager gives a range guidance, I take the mid-point of the range. Capex forecasts tend to have a flavor of tangibility and permanence, as available funds are spent on tangible expansion by purchase of capital assets. Spending on capex also signals that the firm believes that a high state of the world would persist in the future and the net positive opportunity set available is not going to be short term. Compared to earnings or sales forecasts that can be affected by vagaries of short-term goals and exogenous fluctuations, capex forecasts must be well thought out as firms are usually not able to get out of investments quickly. Prior research has also documented that capex forecasts act as a barometer of managerial reputation and capex increases have positive market price reactions[21]. High capex forecasts indicate that the firm's prospects are positive and since capital expenditures disclosures are subject to audit, it signals commitment. I consider annual capex forecasts given by a firm in our main tests. For tests that analyze probability of type of news, I create a variable *NEWS* that takes the value -1 if manager's capex forecast does not exceed analysts' forecast, 0 if there is no disclosure, and 1 if capex forecast exceeds analysts' forecast.

D. Control Variables

I use a battery of control variables informed from existing literature on capex forecasts, product market competition, and labor unions. Following prior studies (Li, 2010; Lu and Tucker, 2012; Bova, 2013, Vashishtha, 2014; Ali and Fan, 2024), I control for size of the firm (*SIZE*) which natural logarithm of firm's market value, Tobin's Q (*TOBINQ*), asset tangibility (*TANGIBLE)*, Herfindahl Hirschman Index (*IND_HHI)*, stock return (*RETURN*), volatility of returns (*RETVOL*), volatility of capital expenditures (*CAPXVOL*), presence of a big 4 auditor (*BIG4*), level of debt (*LEVERAGE)* and a dummy variable if returns in the previous quarter was negative (*BADNEWS*). Table 6 provides summary statistics for the final sample.

[21] See McConnell and Muscarella (1985), Chan et al. (1990, 1994), Hirschleifer (1993), Chung et al. (1997), Brailsford and Yeoh (2004).

Descriptive Statistics

From Table 5 the mean(median) value of *PMF* is 6.36 (5.63) respectively. As a comparison, the mean(median) *PMF* of 6.9(6.3) is reported by Hoberg et al. (2014) for their sample. About 12% (*PSURP*=0.12) of the capex guidance exceeds analysts' forecasts. 52.3% of capex forecasts are point forecasts rather than range forecasts[22]. The mean value of labor related threats- *IMMINENT* is 0.01, and for *LABOR_RISK* and *LRISK* is 2.31 and 0.5 respectively. Mean Tobin's Q (*TOBINQ)* proxying for growth opportunities is 2.27. Mean asset tangibility (*TANGIBLE*) for is 29%. The mean values of industry concentration (*IND_HHI),* 22.47 assure us that our firms operate in markets where there are large number of players. Rest of the controls are *LEVERAGE* (25%), *RETURN* (3%), return volatility- *RETVOL* (0.21), Capex volatility- *CAPEXVOL* (183), *SIZE* (8) and *BADNEWS* (0.43). Finally, most firms (91%) in both samples are audited by a big 4 auditor. Appendix A provides definitions of control variables.

[Table 4 here]

4. Empirical Methodology and Results

Earnings Call Based Binary Measure of Labor Threat

I test the hypothesis that a firm facing competitive threats from existing rivals as well as labor threats is unlikely to withhold good news. I run logistic regression and OLS regression with *PSURP* as dependent variable[23]. I expect that the coefficient on existing competition proxied by *HICOMP,* and labor related threat proxied by *IMMINENT* would have a negative sign and

[22] Ali and Fan (2024) also report that 94% of capex forecasts are annual and 54% of annual forecasts are point forecasts. In our IBES sample 96% of capex forecasts are annual.

[23] I avoid writing *PSURP* in log of odds ratio format, i.e. log(p/1-p) for the sake of brevity.

significant, but their interaction would be positive and significant. The logistic regression specification is as follows-

$$PSURP_{i,t} = \beta_0 + \beta_1 \cdot IMMINENT_{i,t} + \beta_2 \cdot HICOMP_{i,t} + \beta_3 \cdot IMMINENT_{i,t} \cdot HICOMP_{i,t} + \beta_4 \cdot Controls_{i,t} + \gamma_j + \theta_\tau + \epsilon_{i,t}$$

The regression employs industry fixed effects γ_j (Fama-French 48 industry classification), year fixed effects θ_τ to control for time-invariant industry characteristics and time trend due to macroeconomic conditions. Standard errors are adjusted for Newey-West heteroscedasticity and autocorrelation to allow for correlated forecasting behavior across time[24]. Table 5 presents the output of the regression. Columns 1 results for logistic regression without and with controls respectively. In column 1 the coefficient on *HICOMP* is -0.220, significant at 1% level. A firm facing rival action is unlikely to disclose good news. The coefficient on *IMMINENT* (-0.168), although not statistically significant. Now we focus on the interaction term. The interaction term *HICOMP*IMMINENT* is positive (1.215) and statistically significant at 1% level. Thus, a firm facing both labor related threats and product market competition individually is likely to withhold good news, but in their joint presence the firm is unlikely to do so.

[Table 5 here]

To interpret economic significance, I compute predicted probabilities of *PSURP* at various levels of *HICOMP* and *IMMINENT*. Table 6 documents predicted probabilities of *PSURP* at each level of predictor compared to the baseline (*IMMINENT*=0, *HICOMP*=0).

[Table 6 here]

When *HICOMP* changes from 0 to 1, predicted probability of *PSURP* (good news) decreases by 19.4 percentage points and is statistically significant. *IMMINENT* does not seem to impact

[24] Clustering stand errors on firms does not change our coefficients but level of significance drops.

the probability of positive surprises in a statistically significant way, although the direction is negative. The joint presence increases the probability by 14.4 percentage points and is statistically significant at 5% level.

Disclosure Vs Non-Disclosure of Good News and Bad News

So far, only good news disclosures have been analyzed. I abstracted away from bad news disclosures by clubbing firms that do not disclose good and provide bad news disclosures (capex forecast less than analyst's forecasts) together into one category (*PSURP=0)*. Now I turn to analyze the ordinal nature of disclosures- bad news, no disclosure and good news. By doing so, it can be gleaned whether the predictors *HICOMP* and *IMMINENT* affect the probability of moving from one level of news to another. To that end I create an ordinal variable *NEWS* that takes the value -1 for bad news (manager's capex forecasts less than analyst's forecasts), 0 (for no disclosure) and +1, (manager's capex forecasts exceeding analyst's forecasts). A movement from -1 to +1 is deemed to be movement from lower to higher category of news. The following ordinal (ordered) logistic regression with industry-year fixed effects and robust standard errors is employed-

$$\boldsymbol{NEWS_{i,t} = \beta_0 + \beta_1 \cdot IMMINENT_{i,t} + \beta_2 \cdot HICOMP_{i,t} + \beta_3 \cdot IMMINENT_{i,t} \cdot HICOMP_{i,t} + \beta_4 \cdot Controls_{i,t} + \gamma_j + \theta_\tau + \epsilon_{i,t}}$$

Table 7 documents the results of the ordinal logistic regression. The coefficient on *NEWS* is negative and significant. When a firm faces a rival, its disclosure is less likely to be in a 'higher' news category. Similarly, when a firm faces labor threat, it is less likely to disclose in a higher news category, although not significantly so. The presence of competitive threat and labor threat increases the likelihood of a firm's disclosure moving to a 'higher' category.

[Table 7 here]

Table 8 shows probability of a particular news type (bad news, no news, good news) based on the level of predictors.

[Table 8 here]

First, the probabilities are all significantly different from 0. Secondly, probability of a certain type of disclosure (bad, none or good) contingent upon the level of the predictors is in line with expectations. Pr(Bad News | 0,0) < Pr(Bad News | 0,1), 9.04% < 10.92%; Pr(Bad News | 0,0) < Pr(Bad News | 1,0), 9.08% < 11.92%; Pr(Good News | 1,1) > Pr(Good News | 0,1), 18.09% > 10.29%; Pr(Good News | 1,1) > Pr(Good News | 1,0), 18.09% > 9.42%; and finally, Pr(Good News | 1,1) > Pr(Good News | 0,0), 18.99% > 12.36%. Non-disclosure probabilities are remarkably stable, except in the instance of joint presence of labor threats and competitive threat (1,1) where it drops by nearly 3%, suggesting that firms choose to disclose good news rather than withhold it. At this level of the predictors, probability of bad news is 6% whereas that of good news is three times as much.

Finally, in Table 9, I report pairwise comparison of probabilities for good news and bad news. When firm faces a labor threat it has some propensity to disclose bad news and withhold good news, but not significantly so. When faced with competition it has a strong tendency to disclose bad news and withhold good news. But when faced with both the threats firm is significantly less likely to disclose bad news and more likely to disclose good news.

[Table 9 here]

The results from tables 6 to 9 provide a complete picture of the nature of disclosures a firm decides on when faced with multiple recipients with aligned disclosure incentives. Presence of any one entity incentivizes the firm to disclose bad news and withhold good news. But their joint presence incentivizes the firm to do the opposite.

Having found support for extant theory, I further create two new measures of labor related threats- one based on a computational linguistic technique and another from sentiment of labor related news. I apply the former to earnings conference calls and the latter is sourced from Raven Pack Analytics.

5. Robustness Tests

Machine Learning Based Measure of Labor Threat

The keyword/phrase matching approach implemented earlier to create the variable *IMMINENT* from earnings conference call is a rudimentary application that does not consider the labor related risks in the background that firm deals with. The binary nature of *IMMINENT* is such that it captures only the pressing labor threats faced by a firm, and one might have a concern that threat of strikes, mass layoffs, breakdown of negotiations with union etc. individually can also become pressing, without the need to have all of them happening at the same time. To address these concerns, I introduce a machine learning based measure of labor related threat that is continuous and offers an idea of ongoing levels of labor related risks faced by the firm.

We focus on the proportion of conversation around labor related issues in a conference call. Any labor-related issue raised must be of some concern to the firm's management or the analysts participating in the call. In Bag-Of-Words (BOW) approach of matching keywords, we had apriori decided upon a list of words and phrases to search for, based on random readings of earnings conference calls. One might argue that this can create a bias for certain words and phrases, or it is not possible to create an exhaustive list from surveying a small number of call transcripts. So, in ML based measure, I don't decide upon the words beforehand or make exogenous judgement on which words or phrases may be associated with labor related and non-labor related topics. I instead borrow a technique from computational linguistics called pattern-based-sequence-classification (Song and Wu 2008, Manning et al. (2008)). The routine picks up language patterns specific to labor related topics and non-labor related topics, and that allows me to compute the proportion of the conversation devoted to labor related topics in an earnings conference call.

To compute a measure of labor risk, I adapt the methodologies described in Hassan et al. (2018) in which they compute a measure of political risk from earnings call transcripts. I first create a training library of labor bigrams (two-word conjunctions) that are typical of conversations pertaining to labor issues[25]. Then, I extract such labor related bigrams from a textbook on Labor Economics (Contemporary Labor Economics by Connel, Brue and Macpherson, 12E). Similarly, I also create a training library of non-labor bigrams for conversations that are not related to labor issues. For this purpose, I use an MBA level financial accounting textbook (Financial Accounting by Libby, Libby and Hodge, 11E)[26].

Once the training libraries of bigrams is created, each earnings call transcript is decomposed into bigrams. Then the number of occurrences of labor related bigrams within ten words surrounding risk, threat and uncertainty on either side of the bigram is counted by the program, and divided by total number of bigrams in the call transcript. The measure *LABOR_RISK* is given by-

$$LABOR\_RISK_{i,t} = \frac{\sum_{b}^{B_{i,t}}(\boldsymbol{I}[b \in \boldsymbol{L\ but\ not\ N}]).\boldsymbol{I}[|b - risk| < 10].\frac{f_{b,L}}{B_L}}{B_{i,t}}$$

Where, **I[.]** is an indicator function, that takes the value 1 if a bigram is a labor bigram (first term in the numerator), 0 otherwise; takes the value 1 if the distance of the bigram from "risk", "uncertainty" or "threat" is less than 10 words ,0 otherwise (second term of the numerator).

[25] Take for example the bigram *union negotiations*. This bigram is more likely to occur in conversations around labor issues, compared to non-labor issues.

[26] Hassan et al. (2018) uses American Politics Today by Bianco and Canon, 3E for extracting political bigrams and Financial Accounting by Libby, Libby and Short, 7E for extracting non-political bigrams.

The third term $\frac{f_{b,L}}{B_L}$ is the frequency of occurrence of a labor related bigram in the corpus of labor bigrams. In text classification literature, $(\boldsymbol{I}[b \in \boldsymbol{L}\ \boldsymbol{but\ not}\ \boldsymbol{N}]).\frac{f_{b,L}}{B_L}$ is commonly known as Term Frequency- Inverse Document Frequency (TF-IDF) of the bigram. It measures the relative importance of bigrams in a corpus of bigrams. The higher the values of TF-IDF the more important the bigram is within the corpus. The computation above is a standard one in the literature except for our specific conditioning on the existence of bigrams within the context of risk, threat and uncertainty.

The initial measure of labor threat is computed from bigrams of labor economics textbook. We multiply the measure by 10^4 and use the value *LABOR_RISK* in our empirical tests[27]. The meaning of *LABOR_RISK* is 2.3 which is scaled up from 0.00023. The maximum value of *LABOR_RISK* is 48.65 which corresponds to raw score of 0.00486. One can roughly interpret that at the maximum values of labor risk, about 0.5% of the conversation in an earnings call revolves around discussions related to labor related issues. *LABOR_RISK* is split at its sample median to create a binary variable *LRISK* (=1 if values are above media, 0 otherwise) and used in tests. Table 10 provides summary statistics of labor risk measures for our sample.

[Table 10 here]

I test the hypothesis using this machine learning based measure of labor related threat (risk). We employ the following logistic specification-

$$\boldsymbol{PSURP_{i,t}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} \cdot \boldsymbol{LRISK_{i,t}} + \boldsymbol{\beta_2} \cdot \boldsymbol{PMF_{i,t}} + \boldsymbol{\beta_3} \cdot \boldsymbol{LRISK_{i,t}} \cdot \boldsymbol{PMF_{i,t}} + \boldsymbol{\beta_4} \cdot \boldsymbol{Controls_{i,t}} + \boldsymbol{\gamma_j} + \boldsymbol{\theta_\tau} + \boldsymbol{\epsilon_{i,t}}$$

Table 11 Column 1 presents output from logistic regression using *LRISK*. The regressions employ a full set of controls, industry year fixed effects and robust standard errors. The results

[27] This is in line with Hassan et al. (2018). Otherwise, proportions are miniscule of the order 10^{-4} or less.

are in the direction of the predictions. Firm is unlikely to disclose good news when faced with competitive threat, *HICOMP* is negatively significant. Firm is unlikely to disclose good news when faced with labor threat. But the interaction term is positive (0.159) and significant (at 10%), signaling weakening of incentives to withhold good news.

[Table 11 here]

To interpret economic significance, I again compute predicted probabilities at various levels of *HICOMP* and *LRISK*. Table 12 documents predicted probabilities of *PSURP* at each level of predictor compared to baseline (*LRISK*=0, *HICOMP*=0).

[Table 12 here]

The result broadly lines up with the main test with bag of words approach employed earlier. In presence of competition, firm is less likely to disclose good news. When both competition and labor threat are present, firm is likely to disclose good news rather than withhold it. The joint presence of both labor threat and competitive threat significantly increases the probability of good news disclosures.

I again run the ordinal logistic regression to check how the probabilities turn out at each level of disclosure for a given level of predictors. Table 13 provides the output. As before, results continue to hold that supports predictions from theory. The interaction term is significantly positive alluding to manager’s strategic decision to disclose good news when faced with both labor threat and competition.

[Table 13 here]

In Table 14, I compute the predicted probabilities of type of news given the level of competition and labor threat and find them to be statistically different from 0 and largely in line with what one would expect.

[Table 14 here]

Raven Pack News Event Based Measure

Raven Pack Analytics (RPA henceforth) provides detailed analytics of news like sentiment of news articles, impact of news on short term volatility etc. from thousands of different news outlets across 23 categories. I download data pertaining to "labor-issues" for firms in USA. Following prior literature (Bushman & Pinto 2024), I filter out news types that are news flashes and tabular material.[28] The category of labor related issues covers 23 different types of labor related news like layoffs, hirings, compensation, union negotiations, resignations, workforce salary etc. News organizations report about ongoing labor related issues, and the sentiment in such news captures the underlying labor conditions, management- labor relation etc. that the manager of the firm is navigating. Examining the sentiment of the news allows us to look at labor related threats faced by a firm as perceived by media and public. Also, it acts as a proxy for those scenarios in which manager fails to handle labor relayed issue, and it spills into the public domain.

RPA provides a Composite Sentiment Score (CSS) that measures composite story level sentiment of the news item. CSS is a score between -1.00 and +1.00[29], combines various sentiment analysis techniques, including emotionally charged words and phrases, and expert-rated short-term share price impact. CSS strength (above or below 0) is determined using intraday stock price reactions from around 100 large-cap stocks. CSS combines 5 sentiment analytics using rules to ensure no sentiment disagreement exists. Trained on market data, CSS

[28] Unlike Bushman and Pinto (2024), we do not filter out events that have relevance score for firm greater than 75. Relevance score measures how relevant a news event is to a particular firm. Labor related issues tend to have industry specific character and any labor related issue afflicting one or a group of firms in the industry can have a spillover effect on other firms in the industry.
[29] The RPNA4.0 provides CSS scores that are between 0 and 100.

reflects how positive or negative a story is and is typically used for short-term signals in trading strategies. A negative score implies the firm could/is facing labor related issues.

I compute a firm-quarter measure by averaging each of these sentiment scores by firm and quarter across various categories and obtain data for 5251 firms across 63131 quarters. Positive mean scores likely signal hirings, successful union negotiations, better management labor relations etc., while negative mean scores indicate labor related distress, layoffs, strike, etc. Figure 3 shows sample distribution of the measures.

Figure 3 shows that a substantial portion (27%) of labor related news events seem to not elicit any market response as evident from the tall histogram at CSS sentiment score of 0. Again, observations with negative market reaction (20%) are smaller than observations that elicit a positive market reaction (53%).

[Figure 3 here]

To exploit the nuanced understanding of labor related issues afforded by the RPA database, I create binary variable *NEG_CSS*. *NEG_CSS* takes the value 1 if CSS is less than 0. The cases of neutral and positive sentiments are coded as 0. A value of 1 indicates a negative climate and signals that the firm is facing potential labor related threats arising out of issues like strikes, layoffs, unsuccessful union negotiations etc.

Table 15 provides the descriptive statistics of the labor threat measure from Raven Pack data. Slightly above 20% of the observations have overall negative sentiment, proxying for potential labor related threat.

[Table 15 here]

I run the following logistic specification-.

$$\boldsymbol{PSURP_{i,t} = \beta_0 + \beta_1 \cdot NEG\_CSS_{i,t} + \beta_2 \cdot HICOMP_{i,t} + \beta_3 \cdot NEG\_CSS_{i,t} \cdot HICOMP_{i,t}}$$
$$\boldsymbol{+ \beta_4 \cdot Controls_{i,t} + \gamma_j + \theta_\tau + \epsilon_{i,t}}$$

The output for logistic regression with controls, fixed effects and clustering is provided in Table 16. The coefficient on *HICOMP* is -0.298 and is significant at 1% level. The coefficient on labor threat (proxied by negative labor news sentiment) is also negatively significant. The interaction term representing the joint forces is positive and significant (albeit at 10% level).

[Table 16 here]

Table 17 provides results of predicted probabilities of good news based on levels of labor news sentiment and product market competition.

[Table 17 here]

The results from sentiment of labor news as well as manager's own discussion in earning conference calls about the nature of labor related threats that the firm faces collectively supports the prediction of *AR24* that a firm facing threat from labor as well as competition is likely to disclose good news in equilibrium and not withhold it.

[Table 18 here]

Finally, by employing an ordinal logistic regression (Table 18 above) like we did before, we test the likelihood of being at a higher news level conditioned on presence of either of the threats and both the threats. In the ordinal logistic regression, our dependent variable *NEWS* is regressed on *HICOMP* and *NEG_CSS*. The coefficient on individual threats is negative and significant while on interaction term (joint presence of threats) is positive and significant.

Table 19 below presents the predicted probabilities of bad news, non- disclosure and good news based on presence of either of the threats, and joint presence of the threats.

[Table 19 here]

Hamm et al. (2018) Measure of Unionization

As discussed earlier, Hamm et al. (2018) proposed a binary measure of whether a firm is unionized or not. Information about whether employees are unionized or not is given in the firm's annual 10-K filing with the SEC. Following the procedures in Hamm et al. (2018) the measure is constructed through a multistep search logic. First, I search for variations of phrases and key words like "union(s)", "unionization", union(ized), "collective(ly) bargain(ing)", "labo(u)r/employee(s')/worker(s') organization(s) etc. Instances where "union" is followed by "bank" or preceded by "Soviet" etc. are excluded. For all instances captured in the first step, *UNION_DUMMY* is coded as 1, rest is coded as 0. Second, I consider all the instances for which *UNION_DUMMY* is coded as 1 in previous step and search for "No union" expressions like "None of our labor force is covered by a collective bargaining agreement", "We have no unionized employees", "There is no collectively bargained agreement", "A union does not represent any of our" etc. For all such instances where "No union" phrases are found, *UNION_DUMMY* is coded back to 0. Finally, if any of the "No union" expressions from previous step are found with a specific geographic region in the same sentence like "None of our employees in India is unionized", "We have no unionized employees in Europe" etc., then we do not consider it to be "No union" expression and code *UNION_DUMMY* back to 1.[30] A full set of keywords/phrases used is given in Appendix B.

I test our hypothesis again using the binary variable *UNION_DUMMY,* a firm-year measure of unionization instead of *IMMINENT* that we used in our main tests. If a firm is unionized in any given year, *UNION*_DUMMY takes the value 1 for that firm-year observation, 0 otherwise.

[30] For this step, we use Python's Spacy library's GPE (Geographical region) tag for Named Entity Recognition. Documentation available in https://spacy.io/usage/linguistic-features.

Table 20 below presents the results from our logistic regression specification. The coefficient on *HICOMP* and *UNION_DUMMY* is negative and significant at 1% level, while the coefficient on the interaction term *HICOMP* UNION_DUMMY* is positively significant at 5%.

[Table 20 here]

The predicted probabilities of PSURP documented in Table 21 are in line with our hypothesis.

[Table 21 here]

The ordinal logit specification shown in Table 22 shows that in presence of union pressure and competition, firm's disclosures tend to move into higher category (significant at 1% level).

[Table 22 here]

Tables 23 provides predicted probabilities of type of news given the level of predictors. We see that Pr(Good News|1,1)> Pr(Bad News|0,1) and Pr(Good News|1,1)>Pr(Bad News|1,0) which aligns with the prediction that firms facing joint threats have higher tendency to disclose good news rather than bad news.

[Table 23 here]

6. Conclusion

Arya and Ramanan (2024) challenge the prevalent understanding that when incentives are aligned, one directional economic force are additive. I empirically test their theory using a firm's capital expenditure forecasts as proxy for the firm presenting a long term favourable outlook (good news) and find support for their theory. I introduce two new measures of labor related threat using quarterly earnings conference calls and news articles that generalizes the labor related issues faced by a firm beyond organized labor unions. I find that their story holds through alternate measures of labor threats, alternate fixed effects specifications and entropy balanced samples. The theory of a firm's disclosures having direct and indirect effects on multiple recipients can be studied further in variety of settings involving two opponents for whom disclosure incentives are aligned like product market rivals, political costs, regulatory threat, labor unions etc.

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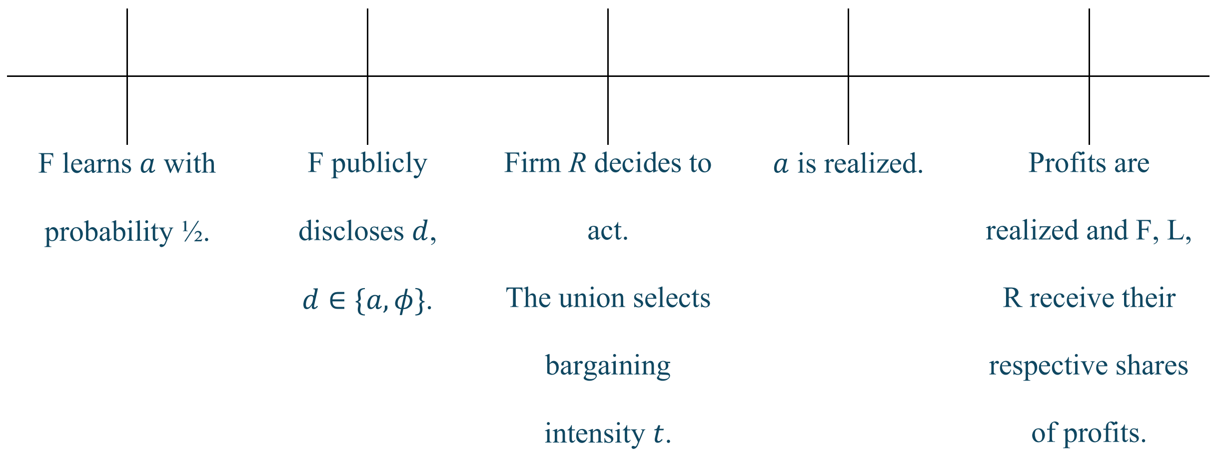
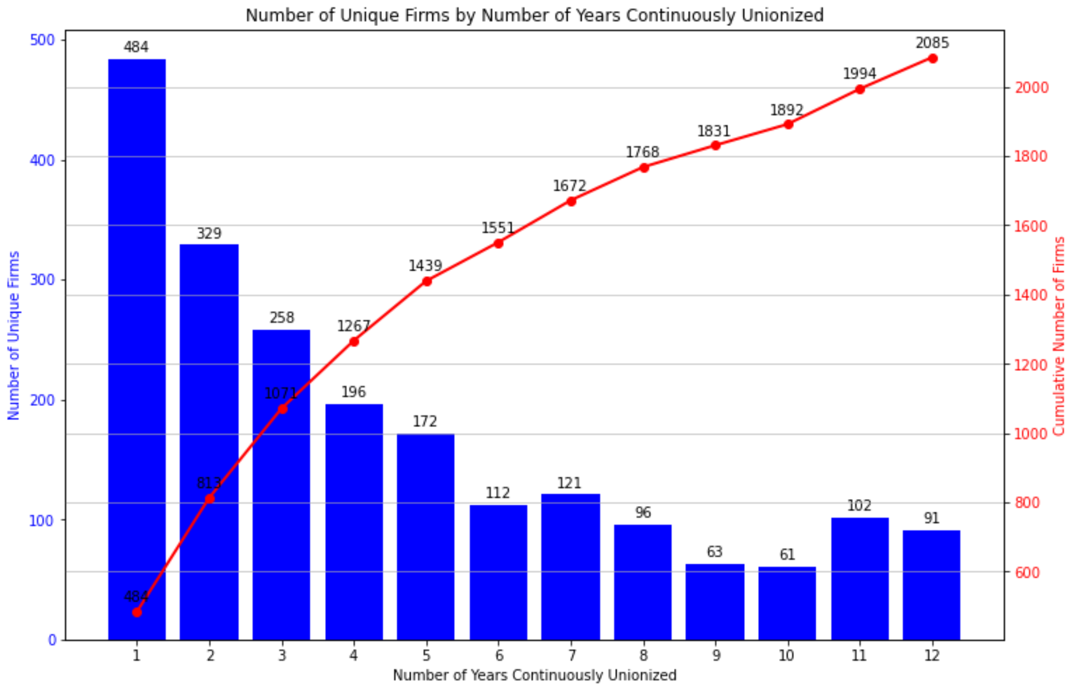
Figure 1. Timeline of the game



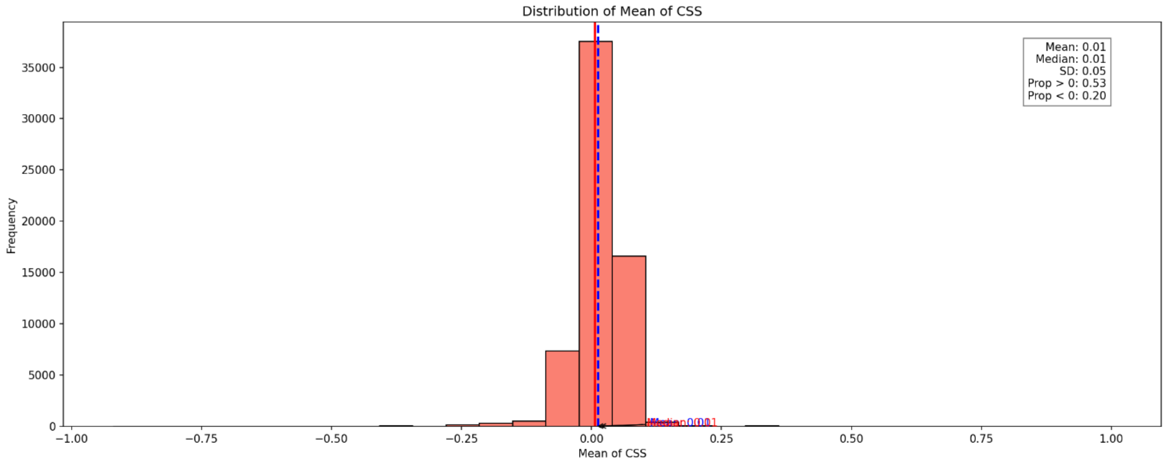
This figure shows the timeline of the game played by firm F, labor union L and the rival R.

Figure 2: Persistence in Unionization Among Unionized Firms in Compustat Sample



This figure shows the persistence of unionization in Compustat Sample for the period 2009-19 for which union related data is available in 10-K reports sourced from Calc Bench. On x-axis we have 'Number of Years Continuously Unionized'. On y-axis to the left we have 'Number of Unique Firms', and to the right we have 'Cumulative Number of Firms'.

Figure 3. Sample Distribution of Means of Composite Sentiment Score (CSS)



This figure shows sample distribution of mean of Composite Sentiment Score (CSS). The x-axis shows the range from -1 (highly negative sentiment) to +1 (highly positive sentiment). Y- axis shows the number of observations.

Table 1. Sample Construction

Particulars	Number of Firms	Observation
A) Compustat Sample	6264	143196
B) IBES Sample	3245	50523
C) Hoberg and Philips Sample	7347	50728
D) Earnings Calls (ECC) Sample	2438	66510
Final Sample: A∩B∩C∩D	**1288**	**33142**

This table shows Sample construction for the tests for the period 2009-19.

Table 2. Set of Keywords for Strikes, Layoffs, Union and Acronyms Names of Labor Unions Obtained from Reading Earnings Conference Calls.

Strike related keywords and phrases: impact of strike, impact of the strike, impacted by strike, impacted by the strike, strike impact, strikes impact, impact from strike, impact from the strike, uaw strike, about strike, ongoing strike, any strike impacts, impacts from the strike, strikes will negatively impact, strikes will cost, strikes to cost, strike to cost, went on a strike, went on strike, called a strike, called strike, strike called by, strikes called by, strikes by union, strike by union, labor strike, union called strike, union called a strike, work stoppage.

Layoff related keywords and phrases: layoffs, lay off, laid off, job cut, down size, downsize, downsizing, down-sizing, right size, right size, right sizing, rightsizing, right-size, hiring freeze, fire, fires, firing, employees.

Union related keywords and phrases: union, collective bargaining, collectively bargain, labour organization, labor organization, employee organization, worker organization.

Acronyms of Labor Unions Names: ATU, OPEIU, AFSCME, CNA, UPTE, UCSW, AFT, BCTGM, CNN, NUHW, IUOE, NNU, IUOE, CTU, SEIU, CWA, IBEW, DFT, GEO, HGSU, UAW, IAM, IAMAW, IBT, IFPTE, ILWU, ILA, BAC, IUPAT, LIUNA, UBC, LCFT, LEAD, MNA, NFLPA, SCTA, ATU, SMART, SMWU, APSCUF, TWU, UICUF, UA, UBT, UE, UFCW, UFCWU, UNITE HERE, USW, USS, UPTE-CWA, UWA, WVEA.

Table 3. Descriptive Statistics of Earnings Conference Call Based Measures

	N	Mean	Std	Min	25%	Median	75%	max
STRIKE	66510	0.10	0.29	0	0	0	0	1
LAYOFF	66510	0.09	0.29	0	0	0	0	1
UNION	66510	0.06	0.24	0	0	0	0	1
IMMINENT	66510	0.01	0.08	0	0	0	0	1

The table shows descriptive statistics of earnings call-based measure of labor threats for the entire Compustat sample from 2009-19.

Table 4. Descriptive Statistics for Merged Compustat/IBES, Earnings Conference Call Sample

variable	N	min	p25	mean	p50	p75	max	sd
PSURP	33142	0.00	0.00	0.12	0.00	0.00	1.00	0.32
NEWS	33142	-1.00	0.00	0.02	0.00	0.00	1.00	0.46
PMF	33142	1.31	3.91	6.36	5.63	8.06	16.27	3.33
HICOMP	33142	0.00	0.00	0.25	0.00	0.00	1.00	0.43
IMMINENT	33142	0.00	0.00	0.01	0.00	0.00	1.00	0.09
TOBINQ	33142	0.79	1.24	2.27	1.67	2.61	9.99	1.67
TANGIBLE	33142	0.01	0.08	0.29	0.19	0.46	0.91	0.26
IND_HHI	33142	6.27	10.32	22.47	10.62	22.00	152.44	25.04
LEVERAGE	33142	0.00	0.10	0.25	0.25	0.37	0.71	0.18
RETURN	33142	-0.51	-0.08	0.03	0.03	0.14	0.73	0.20
RETVOL	33142	0.05	0.12	0.21	0.17	0.25	1.05	0.14
CAPXVOL	33142	0.31	8.01	182.65	28.93	109.28	3441.64	478.31
SIZE	33142	4.89	6.97	8.02	7.84	8.96	12.10	1.50
BIG4	33142	0.00	1.00	0.91	1.00	1.00	1.00	0.28
BADNEWS	33142	0.00	0.00	0.43	0.00	1.00	1.00	0.49

Table 5. Logistic Regression of Good News, Competition and Labor Threats (ECC)

	(1)
VARIABLES	PSURP
HICOMP	-0.220***
	(0.0589)
IMMINENT	-0.168
	(0.217)
HICOMP*IMMINENT	**1.215*** **
	(0.422)
Constant	-5.043***
	(0.214)
Observations	33,142
Industry FE	Yes
Year FE	Yes
Controls	Yes
Clustering	Yes

Robust standard errors in parenthesis. The stars *, ** and *** represent significance at 1%, 5% and 10% respectively. This table presents results from logistic regression for specification-

$$\boldsymbol{PSURP_{i,t} = \beta_0 + \beta_1 \cdot IMMINENT_{i,t} + \beta_2 \cdot HICOMP_{i,t} + \beta_3 \cdot IMMINENT_{i,t} \cdot HICOMP_{i,t} + \beta_4 \cdot Controls_{i,t} + \gamma_j + \theta_\tau + \epsilon_{i,t}}$$

Dependent variable is *PSURP,* that takes the value 1 if management's capex forecasts exceed analyst's consensus forecast, 0 otherwise. *HICOMP* is a binary variable that takes the value 1 if *PMF* is in top quartile, 0 otherwise. *IMMINENT* is a binary variable that takes the value 1 if a firm is facing labor related threats, 0 otherwise. The interaction term *HICOMP*IMMINENT* is the main variable of interest. Regression includes industry fixed effects at Fama French 48 industry classification and year fixed effects.

Table 6. Predicted Probabilities of Good News for Different Levels of Predictors.

	HICOMP=0	HICOMP=1
IMMINENT=0	0	-0.194 (-3.67***)
IMMINENT=1	-0.016 (0.81)	0.144 (2.38**)

The table depicts predicted probabilities of good news (*PSURP)* at various levels of labor threat (*IMMINENT)* and competition *(HICOMP)* compared to the baseline of *HICOMP=0* and *IMMINENT=0*.

Table 7. Ordinal Logistic Regression of Good News, Competition and Labor Threats (ECC)

VARIABLES	(1) NEWS
HICOMP	-0.144***
	(0.0390)
IMMINENT	-0.309
	(0.204)
HICOMP*IMMINENT	**0.902****
	(0.437)
/cut1	-1.146***
	(0.207)
/cut2	3.161***
	(0.208)
Observations	33,142
Industry FE	Yes
Year FE	Yes
Controls	Yes
Clustering	Yes

Robust standard errors in parenthesis. The stars *, ** and *** represent significance at 1%, 5% and 10% respectively. This table presents results from ordinal logistic regression for specification-

$$\boldsymbol{NEWS_{i,t} = \beta_0 + \beta_1 \cdot IMMINENT_{i,t} + \beta_2 \cdot HICOMP_{i,t} + \beta_3 \cdot IMMINENT_{i,t} \cdot HICOMP_{i,t} + \beta_4 \cdot Controls_{i,t} + \gamma_j + \theta_\tau + \epsilon_{i,t}}$$

Dependent variable is *NEWS,* that takes the value 1 if management's capex forecasts exceed analyst's consensus forecast, 0 if the firm makes no disclosure, and -1 if management's capex forecast is below analyst's consensus forecast. *HICOMP* is a binary variable that takes the value 1 if *PMF* is in top quartile, 0 otherwise. *IMMINENT* is a binary variable that takes the value 1 if a firm is facing labor related threats, 0 otherwise. The interaction term *HICOMP*IMMINENT* is the main variable of interest. Regression includes industry fixed effects at Fama French 48 industry classification and year fixed effects.

Table 8. Predicted Probability of News Type Based on Level of Predictors

IMMINENT	HICOMP	Bad News	No News	Good News
0	**0**	0.0904***	0.7857***	0.1239***
0	**1**	0.1092***	0.7879***	0.1029***
1	**0**	0.1192***	0.7867***	0.0942***
1	**1**	0.0598***	0.7593***	0.1809***

Predicted probabilities of news type (Bad News, No- News or non-disclosure and Good News) across various levels of labor threat and competition.

Table 9. Pairwise Comparison of Probabilities of Good News and Bad News

IMMINENT	HICOMP	Bad News	Good News
1	**0**	0.011 (0.66)	-0.004 (-0.2)
0	**1**	0.0119 (3.42***)	-0.013 (-3.56***)
1	**1**	-0.072 (-2.36***)	0.101(1.71*)

This table compares the probabilities of good news (+1) and bad news (-1) across presence or absence of either one of labor threat or competition, and presence of both.

Table 10. Descriptive Statistics of Machine Learning Based Measure of Labor Threat

	N	min	p25	mean	p50	p75	max	sd
LABOR_RISK	33142	0.00	0.00	2.31	1.16	3.32	48.65	3.33
LRISK	33142	0.00	0.00	0.50	0.50	1.00	1.00	0.50

This table shows summary statistics of labor risk measures computed using machine learning approach. *LABOR_RISK* is the raw risk measure and continuous. *LRISK* is a binary measure that splits *LABOR_RISK* at its sample median.

Table 11. Logistic Regression of Competition, Labor Threat (ML based) and Good News

	(1)
VARIABLES	PSURP
HICOMP	-0.293***
	(0.0759)
LRISK	-0.0143
	(0.0400)
HICOMP*LRISK	**0.159***
	(0.0890)
Constant	-5.024***
	(0.215)
Observations	33,142
Industry FE	Yes
Year FE	Yes
Controls	Yes
Clustering	Yes

Robust standard errors in parenthesis. The stars *, ** and *** represent significance at 1%, 5% and 10% respectively. This table presents results from ordinal logistic regression for specification-

$$\boldsymbol{PSURP_{i,t} = \beta_0 + \beta_1 \cdot LRISK_{i,t} + \beta_2 \cdot HICOMP_{i,t} + \beta_3 \cdot LRISK_{i,t} \cdot HICOMP_{i,t} + \beta_4 \cdot Controls_{i,t} + \gamma_j + \theta_\tau + \epsilon_{i,t}}$$

Dependent variable is *PSURP,* that takes the value 1 if management's capex forecasts exceed analyst's consensus forecast, 0 if the firm makes no disclosure, and -1 if management's capex forecast is below analyst's consensus forecast. *HICOMP* is a binary variable that takes the value 1 if *PMF* is in top quartile, 0 otherwise. *LRISK* is a binary variable that takes the value 1 if a firm is facing labor related threats, 0 otherwise. The interaction term *LRISK*HICOMP* is the main variable of interest. Regression includes industry fixed effects at Fama French 48 industry classification and year fixed effects.

Table 12. Predicted Probabilities of PSURP for Various Levels of Predictors

	HICOMP=0	HICOMP=1
LRISK=0	0	-0.019 (-3.75***)
LRISK=1	0.002 (0.48)	0.014 (1.75*)

The table depicts predicted probabilities of good news (*PSURP)* at various levels of labor threat (*LRISK)* and competition *(HICOMP)* compared to the baseline of *HICOMP=0* and *LRISK=0*.

Table 13. Ordinal Logistic Regression of News, Competition and Labor Threat

VARIABLES	(1) NEWS
HICOMP	-0.204***
	(0.0485)
LRISK	-0.0513
	(0.0326)
HICOMP*LRISK	**0.129*** **
	(0.0572)
/cut1	-1.173***
	(0.207)
/cut2	3.133***
	(0.208)
Observations	33,142
Industry FE	Yes
Year FE	Yes
Controls	Yes
Clustering	Yes

Robust standard errors in parenthesis. The stars *, ** and *** represent significance at 1%, 5% and 10% respectively. This table presents results from ordinal logistic regression for specification-

$$NEWS_{i,t} = \beta_0 + \beta_1 \cdot LRISK_{i,t} + \beta_2 \cdot HICOMP_{i,t} + \beta_3 \cdot LRISK_{i,t} \cdot HICOMP_{i,t} + \beta_4 \cdot Controls_{i,t} + \gamma_j + \theta_\tau + \epsilon_{i,t}$$

Dependent variable is *NEWS,* that takes the value 1 if management's capex forecasts exceed analyst's consensus forecast, 0 if the firm makes no disclosure, and -1 if management's capex forecast is below analyst's consensus forecast. *HICOMP* is a binary variable that takes the value 1 if *PMF* is in top quartile, 0 otherwise. *LRISK* is a binary variable that takes the value 1 if a firm is facing labor related threats, 0 otherwise. The interaction term *HICOMP*LRISK* is the main variable of interest. Regression includes industry fixed effects at Fama French 48 industry classification and year fixed effects.

Table 14. Predicted Probabilities of Type of News based on Level of Predictors

LRISK	HICOMP	Bad News	No News	Good News
0	**0**	8.87%***	78.50%***	12.63%***
0	**1**	9.29%***	78.63%***	12.08%***
1	**0**	10.65%***	78.79%***	10.55%***
1	**1**	9.93%***	78.76%***	11.31%***

Predicted probabilities of news type (Bad News, No- News or non-disclosure and Good News) across various levels of labor threat and competition.

Table 15. Descriptive Statistics of Raven Pack News Sentiment Based Measures

	N	Mean	Std	Min	25%	Median	75%	Max
NEG_CSS	63131	0.20	0.40	0	0	0	0	1

This table describes summary statistics of Raven Pack News Analytics based measure of labor threat. *NEG_CSS* is a binary variable that takes the value of 1 if labor related news sentiment is negative (proxying for labor threat), 0 otherwise. The sample covers all labor related news for available Compustat tickers (hand matched) for the period 2009-19 less news flashes and tabular material.

Table 16. Logistic Regression of Good News, Competition and Labor Threats (RPA)

VARIABLES	(1) PSURP
HICOMP	-0.298***
	(0.0757)
NEG_CSS	-0.124**
	(0.0591)
HICOMP*NEG_CSS	**0.257***
	(0.136)
Constant	-6.365***
	(0.660)
Observations	35,332
Industry FE	Yes
Year FE	Yes
Controls	Yes
Clustering	Yes

Robust standard errors in parenthesis. The stars *, ** and *** represent significance at 1%, 5% and 10% respectively. This table presents results from ordinal logistic regression for specification-

$$PSURP_{i,t} = \beta_0 + \beta_1 \cdot NEG\_CSS_{i,t} + \beta_2 \cdot HICOMP_{i,t} + \beta_3 \cdot NEG\_CSS_{i,t} \cdot HICOMP_{i,t} + \beta_4 \cdot Controls_{i,t} + \gamma_j + \theta_\tau + \epsilon_{i,t}$$

Dependent variable is *PSURP,* that takes the value 1 if management's capex forecasts exceed analyst's consensus forecast, 0 if the firm makes no disclosure, and -1 if management's capex forecast is below analyst's consensus forecast. *HICOMP* is a binary variable that takes the value 1 if *PMF* is in top quartile, 0 otherwise. *NEG_CSS* is a binary variable that takes the value of 1 if labor related news sentiment is negative (proxying for labor threat), 0 otherwise. The interaction term *NEG_CSS*HICOMP* is the main variable of interest. Regression includes industry fixed effects at Fama French 48 industry classification and year fixed effects.

Table 17. Predicted Probability of Good News Based on Level of Predictors

	HICOMP=0	HICOMP=1
NEG_CSS=0	0	-0.015 (-3.67***)
NEG_CSS=1	-0.005 (-1.49)	0.016 (1.93*)

The table depicts predicted probability of good news (*PSURP)* at various levels of labor threat (*NEG_CSS)* and competition *(HICOMP)* compared to the baseline of *HICOMP=0* and *NEG_CSS=0*.

Table 18. Ordinal Logistic Regression of NEWS, Competition and Labor Threat

VARIABLES	(1) NEWS
HICOMP	-0.109**
	(0.0462)
NEG_CSS	-0.184***
	(0.0483)
HICOMP*NEG_CSS	**0.180****
	(0.0784)
/cut1	-1.950***
	(0.366)
/cut2	3.365***
	(0.367)
Observations	35,332
Industry FE	Yes
Year FE	Yes
Controls	Yes
Clustering	Yes

Robust standard errors in parenthesis. The stars *, ** and *** represent significance at 1%, 5% and 10% respectively. This table presents results from ordinal logistic regression for specification-

$$NEWS_{i,t} = \beta_0 + \beta_1 \cdot NEG\_CSS_{i,t} + \beta_2 \cdot HICOMP_{i,t} + \beta_3 \cdot NEG\_CSS_{i,t} \cdot HICOMP_{i,t} + \beta_4 \cdot Controls_{i,t} + \gamma_j + \theta_\tau + \epsilon_{i,t}$$

Dependent variable is *NEWS,* that takes the value 1 if management's capex forecasts exceed analyst's consensus forecast, 0 if the firm makes no disclosure, and -1 if management's capex forecast is below analyst's consensus forecast. *HICOMP* is a binary variable that takes the value 1 if *PMF* is in top quartile, 0 otherwise. *NEG_CSS* is a binary variable that takes the value 1 if a firm is facing labor related threats, 0 otherwise. The interaction term *NEG_CSS*HICOMP* is the main variable of interest. Regression includes industry fixed effects at Fama French 48 industry classification and year fixed effects.

Table 19. Predicted Probabilities of Type of News Based on Level of Predictors

NEG_CSS	HICOMP	Bad News	No News	Good News
0	**0**	5.69%***	86.32%***	7.99%***
1	**0**	6.76%***	86.5%***	6.74%***
0	**1**	6.30%***	86.47%***	7.23%***
1	**1**	6.33%***	86.47%***	7.20%***

Predicted probabilities of news type (Bad News, No- News or non-disclosure and Good News) across various levels of labor threat and competition.

Table 20. Logistic Regression of Competition, Good News and Unionization Dummy

VARIABLES	(1) PSURP
HICOMP	-0.288***
	(0.0472)
UNION_DUMMY	-0.304***
	(0.0433)
HICOMP*UNION_DUMMY	**0.271*** **
	(0.100)
Constant	-3.099***
	(0.418)
Observations	78,245
Industry FE	Yes
Year FE	Yes
Controls	No
Clustering	Yes

Robust standard errors in parenthesis. The stars *, ** and *** represent significance at 1%, 5% and 10% respectively. This table presents results from ordinal logistic regression for specification-

$$\boldsymbol{PSURP_{i,t} = \beta_0 + \beta_1 \cdot UNION\_DUMMY_{i,t} + \beta_2 \cdot HICOMP_{i,t} + \beta_3 \cdot UNION\_DUMMY_{i,t} \cdot HICOMP_{i,t} + \beta_4 \cdot Controls_{i,t} + \gamma_j + \theta_\tau + \epsilon_{i,t}}$$

Dependent variable is *PSURP,* that takes the value 1 if management's capex forecasts exceed analyst's consensus forecast, 0 if the firm makes no disclosure, and -1 if management's capex forecast is below analyst's consensus forecast. *HICOMP* is a binary variable that takes the value 1 if *PMF* is in top quartile, 0 otherwise. *UNION_DUMMY* is a binary variable that takes the value 1 if a firm is facing labor related threats, 0 otherwise. The interaction term *UNION_DUMMY*HICOMP* is the main variable of interest. Regression includes industry fixed effects at Fama French 48 industry classification and year fixed effects.

Table 21. Predicted Probabilities of Good News Based on Level of Predictors

	HICOMP=0	HICOMP=1
UNION_DUMMY=0	0	-0.015 (-5.88***)
UNION_DUMMY=1	-0.015 (-6.70***)	0.018 (3.09***)

The table depicts predicted probabilities of good news (*PSURP)* at various levels of labor threat (*UNION_DUMMY)* and competition *(HICOMP)* compared to the baseline of *HICOMP=0* and *UNION_DUMMY=0*.

Table 22. Ordinal Logistic Regression of NEWS, Competition and Unionization Dummy

VARIABLES	(1) NEWS
HICOMP	-0.0660**
	(0.0326)
UNION_DUMMY	-0.131***
	(0.0319)
HICOMP*UNION_DUMMY	**0.224*** **
	(0.0658)
/cut1	-2.408***
	(0.237)
/cut2	2.890***
	(0.238)
Observations	78,825
Industry FE	Yes
Year FE	Yes
Controls	No
Clustering	Yes

Robust standard errors in parenthesis. The stars *, ** and *** represent significance at 1%, 5% and 10% respectively. This table presents results from ordinal logistic regression for specification-

$$\boldsymbol{NEWS_{i,t} = \beta_0 + \beta_1 \cdot UNION\_DUMMY_{i,t} + \beta_2 \cdot HICOMP_{i,t} + \beta_3 \cdot UNION\_DUMMY_{i,t} \cdot HICOMP_{i,t} + \beta_4 \cdot Controls_{i,t} + \gamma_j + \theta_\tau + \epsilon_{i,t}}$$

Dependent variable is *NEWS,* that takes the value 1 if management's capex forecasts exceed analyst's consensus forecast, 0 if the firm makes no disclosure, and -1 if management's capex forecast is below analyst's consensus forecast. *HICOMP* is a binary variable that takes the value 1 if *PMF* is in top quartile, 0 otherwise. *UNION_DUMMY* is a binary variable that takes the value 1 if a firm is facing labor related threats, 0 otherwise. The interaction term *UNION_DUMMY*HICOMP* is the main variable of interest. Regression includes industry fixed effects at Fama French 48 industry classification and year fixed effects.

Table 23. Predicted Probabilities of Type of NEWS Based on Level of Predictors

UNION_DUMMY	HICOMP	Bad News	No News	Good News
0	**0**	5.80%***	86.5%***	7.72%***
1	**0**	6.56%***	86.6%***	6.84%***
0	**1**	6.17%***	86.6%***	7.26%***
1	**1**	5.66%***	86.4%***	7.91%***

Predicted probabilities of news type (Bad News, No- News or non-disclosure and Good News) across various levels of labor threat and competition.

Appendix A. Variables Description

Variable	Description
Main Variables	
PSURP	Binary variable that takes the value of 1 if management forecast exceeds analysts' forecast, 0 otherwise
NEWS	Ordinal variable that takes value -1 if capex forecast is less that analyst’s forecast, 0, if firm does not disclose and 1 if capex forecast exceeds analysts forecast.
PMF	Product market fluidity proxying for competition
UNION_DUMMY	Binary variable that takes the value of 1 if firm is unionized based on text analytics of 10K, 0 otherwise
IMMINENT	Binary variable that takes value of 1 if managers discuss layoff, strike and union, 0 otherwise
NEG_CSS	Binary variable that takes the value of 1 if both CSS score is less than 0, 0 otherwise.
Control Variables	
TOBINQ	(ATQ+(CSHOQ*PRCCQ)-CEQQ)/(ATQ)
IND_HHI	Herfindahl-Hirschmann Index measured at 2 digits industry level.
TANGIBLE	PPENTQ/ATQ
LEVERAGE	(DLTTQ+DLCQ)/ATQ
RETURN	Percentage change in stock price over previous quarter.
RETVOL	Rolling one quarter window standard deviation of stock return
CAPXVOL	Rolling one quarter window standard deviation of capex investments.
SIZE	Natural logarithm of market capitalization
BIG4	Binary variable that takes the value of 1 if firm is audited by a big 4 auditor
BADNEWS	Binary variable that takes the value of 1 if firm made a loss in the previous quarter

Appendix B. Complete list of union and non-union phrases and keywords.

Union Phrases and Keywords	union(s), unionization, unionized, collectively bargain, collective bargaining, labo(u)r organization(s), employee(s') organization(s), worker organization(s), collective agreement(s)
Non-Union Phrases and Keywords	none of our labor force is covered by a collective bargaining agreement, none of our employees is covered by a collective bargaining agreement, we have no unionized employees, there is no collectively bargained agreement, a union does not represent any of our, not party to any collective bargaining agreement, no current u.s.-based employees are unionized, we have no unionized employees in, none of our employees are unionized, union bank, ununionized, none of our employees in mexico are unionized, collective bargaining agreements do not represent, european union, soviet union, credit union, collectively bargained agreements do not represent, employees are not members of, labor force is not member of, non-unionized, non unionized.

Appendix C. Logistic Regression of Good News, Competition and Labor Threats (ECC) Run Separately on Manager's Presentation and Question & Answer Portion of Earnings Call.

VARIABLES	(1) PPT	(2) Q&A
HICOMP	-0.213***	-0.219***
	(0.0587)	(0.0588)
IMMINENT_PPT	0.158	
	(0.347)	
IMMINENT_Q&A		-0.379
		(0.314)
HICOMP*IMMINENT_PPT	**0.546**	
	(1.356)	
HICOMP*IMMINENT_Q&A		**1.084****
		(0.543)
Constant	-4.373***	-4.362***
	(1.113)	(1.113)
Observations	33,142	33,142
Industry FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes
Clustering	Yes	Yes

Robust standard errors in parenthesis. The stars *, ** and *** represent significance at 1%, 5% and 10% respectively. This table presents results from ordinal logistic regression for specifications in columns 1 and 2 respectively-

$$\boldsymbol{PSURP_{i,t} = \beta_0 + \beta_1 \cdot IMMINENT\_PPT_{i,t} + \beta_2 \cdot HICOMP_{i,t} + \beta_3 \cdot IMMINENT\_PPT_{i,t} \cdot HICOMP_{i,t} + \beta_4 \cdot Controls_{i,t} + \gamma_j + \theta_\tau + \epsilon_{i,t}}$$

$$\boldsymbol{PSURP_{i,t} = \beta_0 + \beta_1 \cdot IMMINENT\_Q\&A_{i,t} + \beta_2 \cdot HICOMP_{i,t} + \beta_3 \cdot IMMINENT\_Q\&A_{i,t} \cdot HICOMP_{i,t} + \beta_4 \cdot Controls_{i,t} + \gamma_j + \theta_\tau + \epsilon_{i,t}}$$

Dependent variable is *PSURP,* that takes the value 1 if management's capex forecasts exceed analyst's consensus forecast, 0 if the firm makes no disclosure, and -1 if management's capex forecast is below analyst's consensus forecast. *HICOMP* is a binary variable that takes the value 1 if *PMF* is in top quartile, 0 otherwise. *IMMINENT_PPT and IMMINENT_Q&A* are binary variables that takes the value 1 if a firm is facing labor related threats, 0 otherwise. The interaction terms *IMMINENT_PPT*HICOMP* and *IMMINENT_Q&A* are the main variables of interest in both columns 1 and 2 respectively. Both the columns includes industry fixed effects at Fama French 48 industry classification and year fixed effects.