Technological Change and the Information Content of Labor Force Restructuring

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Abstract

How do new technologies affect firms' labor force restructuring decisions? I develop a model in which layoffs are strategic choices under asymmetric information about the motive for restructuring, and show that a technological regime shift reduces the informational discount associated with layoff announcements by inducing more high-type firms to enter the layoff pool. I test this mechanism using the introduction of ChatGPT as a GenAI regime shift, and find that firms with greater AI capital are 55–64% more likely to conduct layoffs and earn announcement returns that are 5–10 percentage points higher. Consistent with the information channel, these effects are attenuated among opaque firms and are expected to be absent in placebo tests using private firms. Finally, firms with greater AI capital do not disproportionately displace AI-exposed workers, indicating that these layoffs are not explained by canonical task substitution.

Keywords: Layoffs; Artificial intelligence; Organizational capital; Information asymmetry; Managerial incentives

JEL: D82, G14, G34, J63, O33

1 Introduction

Technological advancement has long disrupted the labor market and has contributed to wage inequality, job polarization, and the displacement of routine work (Autor, Levy, and Murnane, 2003; Goos and Manning, 2007; Acemoglu and Restrepo, 2020). More recently, the emergence of generative artificial intelligence (GenAI) has raised concerns about a new wave of labor market disruption, and mounting evidence already suggests meaningful employment effects. For example, Brynjolfsson, Chandar, and Chen (2025) document a 16% decline in employment among the occupations most exposed to AI, while roughly 20% of U.S. layoffs announced in October 2025 explicitly cited AI as a reason for workforce reductions (The Economist, 2026). Despite these developments, little is known about the determinants of firms' AI-related restructuring decisions. Existing explanations primarily attribute such layoffs to productivity improvements and labor substitution (Acemoglu

and Autor, 2011; Hampole et al., 2025). However, recent large-scale survey evidence presents a puzzle. Although firms increasingly cite AI in layoff announcements, executives overwhelmingly report that AI has had little impact on their firms' productivity to date (Yotzov et al., 2026). This disconnect raises a natural question: why are firms conducting layoffs before the productivity benefits of AI have materialized?

This paper examines whether changes in the informational environment surrounding AI adoption affect firms' layoff decisions. Layoffs have long been associated with financial distress and are generally accompanied by negative stock market reactions (Ofek, 1993; Kang and Shivdasani, 1997; Palmon, Sun, and Tang, 1997; Chen et al., 2001). One reason is that investors cannot directly observe whether a layoff reflects an efficient organizational restructuring or a response to deteriorating business conditions. Consequently, layoff announcements often lead investors to infer that a firm faces underlying problems. I refer to this negative inference as the *stigma* of layoffs. Prior research suggests that managers internalize how observable actions are interpreted by investors and other market participants (Holmström, 1999; Graham, Harvey, and Rajgopal, 2005). As a result, concerns about market reactions may discourage firms from undertaking layoffs even when restructuring would improve organizational efficiency.

I argue that the emergence of a new general-purpose technology can alter this equilibrium. A defining feature of general-purpose technologies is that their value is realized not through adoption alone but through complementary organizational investments and the accumulation of intangible capital (Bresnahan and Trajtenberg, 1995; Brynjolfsson and Hitt, 2000; Bresnahan, Brynjolfsson, and Hitt, 2002; Brynjolfsson, Rock, and Syverson, 2021). Indeed, a substantial share of firm value is attributable to organizational capital and intangibles that must be reconfigured when production technologies change (Eisfeldt and Papanikolaou, 2013; Crouzet et al., 2022). As a result, layoffs become more difficult for investors to interpret: a layoff announcement may reflect a value-enhancing reorganization enabled by the new technology rather than financial distress (Farber and Hallock, 2009). This interpretation reduces the negative inference attached to layoffs, weakening the stigma associated with restructuring. As the expected market penalty declines, more healthy firms find it optimal to undertake layoffs, further improving the average quality of firms announcing layoffs. Consequently, restructuring activity increases and announcement returns improve even before measurable productivity gains emerge.

To test this channel, I exploit the introduction of ChatGPT in late 2022 as a technological regime shift and combine it with cross-sectional variation in firms' AI credibility. I proxy for AI credibility with a firm's stock of AI human capital from Babina et al. (2024). This measure can be viewed as capturing complementary organizational capabilities that facilitate reorganization around new technologies (Crouzet et al., 2022). I complement this measure with occupation-based AI exposure measures from Eisfeldt et al. (2026) and data-asset measures constructed from 10-K filings following Hoberg and Phillips (2016). Using a sample of Compustat firms from 2020 to 2025 comprising 77,695 firm-quarter observations and 949 layoff events identified from SEC EDGAR 8-K filings, I employ a difference-in-differences design that compares AI-credible and non-credible

firms around the introduction of ChatGPT. I first document that AI-credible firms are 55–64% more likely to conduct layoffs following the shock. I also find that layoff announcements by these firms earn cumulative abnormal returns that are 5–10 percentage points higher. The effect is economically meaningful, corresponding to approximately $400–900 million in equity value for the average firm.

These baseline results on their own are also consistent with explanations that involve no informational friction, most notably pure cost savings from AI adoption. I therefore provide a series of tests that speak directly to the information channel. First, the channel predicts that the effect should be weaker among opaque firms, since investors in such firms face greater difficulty updating their beliefs in response to the technological shock. Consistent with this prediction, I find that a one-interquartile increase in opacity attenuates roughly 20% of the baseline announcement-return effect. Second, because the stigma operates through managers' sensitivity to the market's interpretation of their actions, the effect should be stronger for managers who are more sensitive to stock price movements, such as those close to vesting schedules (Edmans, Fang, and Lewellen, 2017) or younger managers who face greater career concerns (Prendergast and Stole, 1996). Empirically, I will proxy for these incentives primarily with CEO tenure and the vesting schedule of equity awards. I expect the layoff and valuation responses to concentrate among managers facing higher reputational stakes: because these managers were the most deterred by the baseline stigma, they have the most to gain from the market's reinterpretation of layoffs.

A remaining concern is that AI-credible firms are simply replacing AI-exposed workers (Brynjolfsson, Chandar, and Chen, 2025; Hosseini Maasoum and Lichtinger, 2025), in which case the results would reflect task substitution rather than any change in market beliefs. Hence, I directly show that AI-credible firms do not disproportionately reduce employment in AI-exposed occupations, which helps rule out direct replacement of AI-exposed workers. Finally, I plan a comparison using private firm layoffs. Credible private firms should also respond to the higher restructuring surplus that the new technology delivers, but because they are not subject to market-based stigma, the information channel predicts that the stigma-driven expansion of layoffs observed among public credible firms should be muted among their private counterparts. Cost-saving and substitution explanations, by contrast, predict responses of similar magnitude regardless of listing status, so the public–private difference in the credible-firm response helps isolate the informational component.

This paper contributes to several strands of literature. First, it contributes to the literature on the real effects of financial markets on corporate decisions. A large body of work documents that the information embedded in stock prices, and managers' anticipation of how the market will interpret their actions, feed back into real choices regarding investment (Holmström and Tirole, 1993; Chen, Goldstein, and Jiang, 2007), acquisitions (Edmans, Goldstein, and Jiang, 2012), and corporate policy more broadly (Bond, Edmans, and Goldstein, 2012). I extend this literature to the restructuring margin by showing that market stigma can distort layoff decisions, leading firms to retain organizational slack that they would otherwise shed. Moreover, I show that technological change can partially alleviate this friction, since a shift in the technological regime alters how

investors interpret restructuring activities and thereby relaxes the informational constraint on managers.

Second, this study contributes to the literature on the valuation effects of technological change. Existing research finds that technology shocks affect firm value through systematic risk (Pástor and Veronesi, 2009), through the reallocation of value toward firms holding growth opportunities (Kogan and Papanikolaou, 2014), and through the displacement risk that new technologies impose on the labor that firms employ (Knesl, 2023). In these frameworks, technology affects prices by changing cash flows or discount rates. I propose an additional and complementary channel whereby technology affects firm value through changes in the market's interpretation of corporate restructuring decisions: the same announcement conveys different information about firm type across technological regimes, so valuation effects can arise even holding the firm's fundamentals fixed.

Third, I contribute to the emerging literature on the employment effects of AI (Brynjolfsson, Li, and Raymond, 2025; Noy and Zhang, 2023; Peng et al., 2023; Humlum and Vestergaard, 2025; Yotzov et al., 2026) by providing a framework that reconciles rising AI-related layoffs with the absence of realized productivity gains. Importantly, the mechanism is not specific to AI. Any general-purpose technology arrives with a lag between adoption and measured productivity, as complementary organizational investments take time to build (David, 1990; Brynjolfsson, Rock, and Syverson, 2021); the framework predicts that it is precisely during this pre-materialization window that the informational content of restructuring shifts and strategically motivated layoffs expand. The findings therefore suggest that new technologies can affect employment outcomes through informational and organizational channels well before productivity improvements appear, a pattern that the framework predicts should recur across general-purpose technology episodes.

Finally, this paper relates to the literature on managerial incentives and short-termism. Theoretical work shows that managers who care about the market's current assessment rationally distort real decisions to influence that assessment (Narayanan, 1985; Stein, 1988, 1989; Holmström, 1999), and survey and empirical evidence confirm that executives sacrifice long-run value to manage market perceptions, particularly when equity incentives are short-horizoned (Graham, Harvey, and Rajgopal, 2005; Edmans, Fang, and Lewellen, 2017) or when firms face public-market scrutiny that their private counterparts do not (Asker, Farre-Mensa, and Ljungqvist, 2015). I add restructuring to the set of real decisions distorted by such concerns, in that the stigma of layoffs deters value-enhancing reorganization, and this distortion operates partly through managerial incentives rather than firm fundamentals alone. My framework further implies that technological change can relax this short-termist distortion by reshaping the market's interpretation of observable corporate actions.

2 Theoretical Framework

In this section, I propose a sequential game with incomplete information to formalize the channel. The timeline is as follows: at $t = 0$, a technological regime $S \in \{\text{Low}, \text{High}\}$ is realized,

and nature draws the firm type $D_i \in \{0, 1\}$, with prior probability $\pi \equiv P(D_i = 1)$, together with the firm's organizational slack ε_i. The type $D_i = 1$ designates a distressed ("low-type") firm: for such a firm, a layoff cuts into healthy operations and destroys long-run value, whereas for a high-type firm ($D_i = 0$) a layoff sheds genuine slack. The firm privately observes (D_i, ε_i) before choosing a layoff intensity $L_i \geq 0$. At $t = 1$, investors observe whether a layoff was announced, $\tilde{L}_i = \mathbf{1}\{L_i > 0\}$, together with the announced scale of the workforce reduction, but they cannot observe D_i or ε_i; they update their beliefs about D_i from the decision to restructure. The restructuring surplus available to firm i is

$$\gamma_i = \bar{\gamma}(S, \theta_i) + \varepsilon_i, \qquad \varepsilon_i \sim \mathcal{N}(0, \sigma_i^2), \tag{1}$$

where $\bar{\gamma}(S, \theta_i)$ is the expected restructuring surplus, $\theta_i \in \{0, 1\}$ indicates observable technological credibility, and σ_i governs the dispersion of the privately observed surplus and thereby the informativeness of the layoff decision. The two latent states play distinct roles: ε_i is the continuous slack draw that determines whether restructuring is worthwhile and is interpreted empirically as the wedge between potential and realized organizational efficiency, while D_i is the binary type that investors infer from the layoff, since they cannot observe whether a cut shed genuine slack or instead damaged healthy operations. The stigma arises precisely because the market fears the latter.

A shareholder-value-maximizing manager chooses L_i to solve

$$\max_{L_i \geq 0} \ \gamma_i L_i + \phi D_i L_i - \frac{c}{2} L_i^2 - \lambda P(D_i = 1 \mid \tilde{L}_i, S, \theta_i) L_i, \tag{2}$$

where $\phi > 0$ captures the additional short-run marginal benefit that a distressed firm derives from cutting payroll (e.g. due to cash-flow pressure) so that low-type firms have stronger private incentives to lay off even though the cut damages healthy operations. The label "value-destroying" therefore refers to the layoff's effect on long-run firm value, which is what investors price, rather than to the manager's flow payoff; this is precisely why distressed firms restructure despite the damage and why the market discounts the announcement. The parameter $c > 0$ governs the convex implementation cost, and $\lambda P(D_i = 1 \mid \tilde{L}_i, S, \theta_i)$ is the per-unit valuation effect of the informational discount. Two features of the information structure are worth noting. First, because investors observe the announced scale of the reduction, I assume the market discount applies proportionally to that scale—larger cuts expose more of the firm's operations to the suspected damage—while beliefs about the firm's *type* are updated from the extensive margin alone; this assumption keeps the pricing rule tractable and matches the empirical practice of measuring announcement returns around disclosed workforce reductions. Second, because credibility θ_i is publicly observable, investors' beliefs and the equilibrium cutoff condition on it throughout. The parameter λ captures the extent to which managers internalize the market's inference about firm type and is naturally larger for managers with stronger career or equity-based incentives.

The optimal layoff policy is characterized by the threshold rule

$$L_i > 0 \iff \gamma_i + \phi D_i \geq \gamma^*(S, \theta_i), \tag{3}$$

where the equilibrium cutoff satisfies

$$\gamma^*(S, \theta_i) = \lambda P(D = 1 \mid \tilde{L} = 1, S, \theta_i). \tag{4}$$

The equilibrium is therefore a Bayesian fixed point: the posterior on the right-hand side is computed from the threshold behavior of both types given the prior π, while the threshold in turn depends on the posterior. Because the posterior is continuous and bounded in the cutoff, standard arguments deliver existence of an equilibrium cutoff.

Substituting $\gamma_i = \bar{\gamma}(S, \theta_i) + \varepsilon_i$ with $\varepsilon_i \sim \mathcal{N}(0, \sigma_i^2)$ yields the layoff probability

$$P(L > 0 \mid D, S, \theta_i) = 1 - \Phi\left(\frac{\gamma^*(S, \theta_i) - \bar{\gamma}(S, \theta_i) - \phi D}{\sigma_i}\right). \tag{5}$$

The key technological assumption is that the regime shift raises the expected restructuring surplus for credible firms, $\bar{\gamma}(\text{High}, 1) > \bar{\gamma}(\text{Low}, 1)$, which is consistent with the finding that major technological breakthroughs create value through complementary organizational investments rather than technology adoption alone (Bresnahan and Trajtenberg, 1995; Brynjolfsson, Rock, and Syverson, 2021). The effect of the shift on the informational discount operates through Bayes' rule, in that the posterior odds of a value-destroying cut conditional on a layoff equal the prior odds multiplied by the likelihood ratio $P(L > 0 \mid D = 1)/P(L > 0 \mid D = 0)$, so the stigma weakens if and only if the regime shift raises high-type participation by proportionally more than low-type participation. I therefore maintain throughout the cutoff configuration in which low-type firms lay off with substantially higher baseline probability than high-type firms—that is, ϕ is large relative to σ_i, so that most of the low-type firms lies above the equilibrium cutoff. In this empirically relevant region, an increase in $\bar{\gamma}$ leaves low-type participation nearly unchanged, since those firms already restructure, while drawing a discrete mass of high-type firms into the layoff pool. Hence, the likelihood ratio falls, the posterior probability of a value-destroying cut conditional on a layoff—the informational discount—declines under the High regime, the stigma weakens, and the restructuring region widens for credible firms.

The model delivers four baseline predictions.

1. *Proposition 1* (*Layoff Expansion*). Credible firms are more likely to conduct layoffs following the technological regime shift,

   $$L_i^*(\text{High}) > L_i^*(\text{Low}),$$

   because the reduction in the informational discount lowers the equilibrium restructuring threshold and widens the restructuring region.

2. *Proposition 2* (*Valuation Effect*). Layoff announcements by credible firms receive more favorable stock market reactions because the regime shift weakens the adverse inference associated with layoffs, reducing the informational discount

   $$\lambda\, P(D_i = 1 \mid \tilde{L}_i = 1, S, \theta_i)\, L_i.$$

3. *Proposition 3* (*Opacity Effect*). Greater information asymmetry attenuates the response of investors' beliefs to the technological regime shift. Define

$$\Delta P_i \equiv P(D_i = 1 \mid \tilde{L}_i = 1, \text{High}, \theta_i) - P(D_i = 1 \mid \tilde{L}_i = 1, \text{Low}, \theta_i), \qquad \frac{\partial |\Delta P_i|}{\partial \sigma_i} < 0,$$

with $\Delta P_i \to 0$ as $\sigma_i \to \infty$. Intuitively, when the surplus draw is highly dispersed, the layoff decision reveals little about the firm's type, so beliefs respond only weakly to the regime shift, attenuating both the valuation effect and the increase in layoff activity.

4. *Proposition 4* (*Managerial Incentives*). The response to the technological regime shift is stronger for managers with higher managerial incentives. Because λ governs the extent to which managers internalize the market's inference about firm type, managers facing stronger reputational concerns or greater equity-based incentives are more deterred by the baseline stigma and therefore respond more strongly to its reduction.

Taken together, these predictions discriminate the information channel from a pure cost-saving explanation, under which there should be no role for managerial incentives or for the firm's information environment. Two clarifications are worth noting. First, private firms serve as a natural placebo, since they face no market-based stigma and hence $\lambda = 0$. Although private credible firms may still increase layoffs owing to the higher restructuring surplus $\bar{\gamma}(\text{High}, 1)$, the absence of the valuation effect—and of the layoff expansion it induces—among private firms isolates the informational channel. Second, in the empirical analysis I interpret analyst forecast dispersion as a reduced-form proxy for the informational friction that σ_i captures, while acknowledging that dispersion also reflects fundamental uncertainty; I discuss this in more detail in Section 3. Finally, for cost savings to confound the results, it would have to be the case that credible firms' layoffs reflect the direct substitution of workers with AI and that these firms also tend to be less opaque. Though this is unlikely, I provide a direct test of the task-substitution mechanism by observing the occupational composition of layoffs: whereas the task-substitution framework (Acemoglu and Autor, 2011; Hampole et al., 2025) predicts that credible AI adopters disproportionately displace AI-exposed workers, the information channel makes no such prediction, since restructuring is motivated by the informational value of reorganization rather than by the comparative advantage of AI in particular tasks.

3 Data and Empirical Strategy

To test these predictions, I construct a sample of Compustat firms from 2020 to 2025, yielding 77,695 firm-quarter observations across 949 layoff events. Layoff events are identified from SEC EDGAR 8-K filings, which provide the most systematic record of formal restructuring announcements for public firms; employee-level characteristics, including occupation-level AI exposure and job-posting activity, come from Revelio Labs; firm-level financial and accounting variables are

from CRSP/Compustat; and analyst forecast data used to construct opacity proxies are from LSEG I/B/E/S. Table 1 reports summary statistics for the estimation sample.

The central empirical challenge is that AI adoption is both unobservable to the econometrician and endogenously determined, in that firms with greater AI capital may differ from other firms along dimensions correlated with both layoff behavior and announcement returns. A particular concern, raised naturally by the cost-saving alternative, is that AI-capital-rich firms may simply face lower labor adjustment costs because AI substitutes more readily for their workers, under which account the higher layoff probability and positive announcement returns would arise with no informational friction at all. To separate the information channel from alternatives, I exploit the introduction of ChatGPT in November 2022 as a technological regime shift towards GenAI that exogenously raised the expected restructuring surplus for firms with pre-determined high AI capital, making these firms susceptible to the reduction in stigma. The identifying assumption is that, absent the shock, AI-credible and non-credible firms would have followed parallel trends in layoff behavior and announcement returns. I estimate two complementary specifications of

$$Y_{it} = \mu_{it} + \beta \left(\text{Post}_t \times \text{AICredible}_i\right) + \gamma' X_{i,t-1} + \varepsilon_{it}, \tag{6}$$

where Y_{it} is either a layoff indicator or the announcement CAR, Post_t marks the post-ChatGPT period, AICredible_i indicates firms in the top quartile of an AI-credibility measure computed over the pre-ChatGPT period and held fixed thereafter, and $X_{i,t-1}$ is a vector of lagged firm controls (size, book leverage, and cash-to-assets), with standard errors clustered at the firm level. In the first specification, μ_{it} comprises industry $\times$ quarter fixed effects, so that β is identified from comparisons of credible and non-credible firms within the same industry-quarter cell and common industry shocks are absorbed; in the second, μ_{it} comprises firm and quarter fixed effects, so that β is identified from within-firm changes around the shock and time-invariant firm heterogeneity is absorbed. The two designs address distinct confounds, and I plan to report specifications that include both sets of fixed effects jointly as an additional robustness check. Because the November 2022 shock coincided with monetary tightening and the normalization of pandemic-era employment—forces that could differentially affect digitized, human-capital-intensive firms even within narrow industries—I also plan to report dynamic event-study estimates with joint pre-trend tests, anticipation windows, and stable-sample exercises to support the parallel-trends assumption directly.

I construct three proxies for AI credibility, each capturing a distinct dimension of a firm's capacity to translate the shock into restructuring surplus, namely AI Capital from Babina et al. (2024), AI Exposure from Eisfeldt et al. (2026), and Data Assets from Hoberg and Phillips (2016). Because these measures capture distinct forces—human capital, task exposure, and textual disclosure, respectively—agreement across them is itself informative about robustness. Because the channel operates through market beliefs, what matters is not the firm's true AI adoption but the information observable to investors, which justifies these publicly visible proxies. Although the market may itself disagree about which firms are AI-credible, this disagreement is what gives the channel scope to operate, since a layoff announcement partially resolves the market's uncertainty about whether

the firm can productively reorganize.

Announcement returns are cumulative abnormal returns computed relative to a market-model benchmark estimated over a pre-event window, with CAR$(-1, +1)$ as the baseline event window; some specifications reported below use alternative event windows. Because 8-K filings may miss some layoff announcements, I corroborate the event sample with plant-level WARN (Worker Adjustment and Retraining Notification) notices from Revelio Labs, and I aim to further validate the events against the "Discontinued Operations/Downsizings" subcategory of S&P Capital IQ's Key Developments database, following Guenzel, Hamilton, and Malmendier (2023). It is worth noting that, because the theory itself predicts that the shock changes which firms select into the layoff pool, event-only regressions combine the repricing of comparable layoffs with an endogenous shift in event composition. I therefore plan a joint analysis of layoff selection and conditional CARs, using reweighting to hold the composition of announcing firms fixed, in order to disentangle the two.

The key challenge in the empirical design is to isolate the information channel, since higher announcement returns and more layoffs are, on their own, also consistent with pure cost-cutting or with layoffs genuinely driven by AI replacing workers. I provide several tests to further strengthen the mechanism. The first tests the opacity prediction: the idea of Proposition 3 is that firms with a poor information environment benefit less from the shock even if they hold high AI capital, since belief updating is more cumbersome for their investors. I follow Jin and Myers (2006) and measure opacity as the dispersion in analyst EPS forecasts, with higher dispersion indicating greater information asymmetry, and I interact AI credibility with opacity to assess whether the valuation effect is attenuated for more opaque firms. Because forecast dispersion also reflects fundamental uncertainty and earnings volatility, I plan to control for these directly and to examine alternative opacity proxies, such as bid-ask spreads and disclosure quality, so that the interaction is not driven by fundamentals rather than the information environment.

The second test interacts AI credibility with managerial incentives. I proxy for these primarily with CEO tenure, since shorter-tenured managers have less-established reputations and more sensitive to belief updates about reputation (Prendergast and Stole, 1996), and with the vesting schedule of equity awards (Edmans, Fang, and Lewellen, 2017), which most directly isolates managers' sensitivity to short-run price movements. Analyst coverage offers a complementary measure of how closely the market scrutinizes the firm and therefore how much reputational capital is at stake in any observable action. It is worth noting that, because coverage also shapes the firm's information environment and is mechanically related to the dispersion-based opacity measure, it cannot by itself separate the incentive channel of Proposition 4 from the opacity channel of Proposition 3. I therefore treat coverage as supplementary and rely on tenure- and vesting-based proxies for the sharper test. The model predicts that the stigma reduction concentrates among high-reputation-stake managers, which addresses the concern that rational managers should attend only to fundamental value, since under career concerns (Holmström, 1999; Stein, 1989) managers rationally respond to the market's interpretation because it affects their future prospects.

A remaining concern is an alternative story of task substitution, which I address directly by

examining the occupational composition of layoffs, as discussed in Section 4. To further probe the mechanism, I plan a placebo test using WARN notices from Revelio Labs employment data, which track layoff events for both public and private firms, to construct a matched sample of private firms. As discussed in Section 2, private firms serve as a natural placebo since they face no market-based stigma. Although private credible firms may still increase layoffs owing to the higher restructuring surplus, the stigma-driven expansion should be muted relative to their public counterparts, whereas cost-saving and task-substitution explanations predict responses of similar magnitude regardless of listing status. Because public and private firms differ along dimensions that matching can mitigate but not eliminate, I interpret this evidence jointly with the opacity and incentive tests.

4 Results and Discussion

In this section, I will briefly discuss the preliminary findings and future directions of the paper. First, regarding the probability of conducting a layoff, Table 2 shows that AI-credible firms are significantly more likely to announce layoffs following the introduction of ChatGPT, with a coefficient of 0.6–0.7 percentage points on the interaction term across all three credibility proxies, corresponding to a 55–64% increase in restructuring activity among credible firms. These magnitudes are stable whether the specification absorbs industry $\times$ quarter fixed effects or firm and quarter fixed effects, and thus do not merely reflect a secular rise in layoffs, common industry shocks, or time-invariant firm heterogeneity. Second, regarding announcement returns, Table 3 shows a 5–10 percentage point increase in announcement CARs for credible firms, equivalent to roughly \$400–900 million in equity value for the average firm, with the effect strongest and most precisely estimated for AI Capital at 5.6–10.8 percentage points depending on the specification, while AI Exposure and Data Assets yield weaker but directionally consistent results. This ordering is itself informative, since AI Capital most directly measures the human-capital complementarities that the general-purpose technology literature identifies as the source of restructuring surplus. Because CARs are observed only at layoff events, the firm-fixed-effect estimates draw identifying variation from firms with repeated layoffs across the sample period and should be read as within-firm repricing among repeat announcers, while the industry $\times$ quarter columns recover the cross-sectional effect.

The opacity test already provides direct support for the information channel as distinct from alternatives, in that the preliminary results (Table 4) show that a one-interquartile increase in opacity attenuates approximately 20% of the baseline return effect, with a significant coefficient on the After $\times$ AICredible $\times$ Opacity interaction, and that the attenuation operates on layoff probability as well, consistent with the prediction that opaque firms cannot communicate their type to investors and therefore benefit less from the stigma reduction. Because forecast dispersion also reflects fundamental uncertainty, the robustness exercises described in Section 3—controlling for earnings volatility and using alternative opacity proxies—are an important complement to this result. The managerial-incentive and organizational-slack interactions remain to be estimated. Based on the model, I expect the layoff and valuation responses to concentrate among high-slack credible firms

and among managers facing higher reputational stakes. Specifically, I expect the triple interaction of Post-ChatGPT, AI credibility, and short CEO tenure or imminent vesting to enter positively in both the layoff-probability and announcement-return regressions. If confirmed, this would be valuable evidence, since a pure cost-saving channel implies no role for managerial reputation beyond mechanical labor-cost effects, whereas the information channel predicts both.

The employee-composition result (Figure 1) is crucial, in that it distinguishes my results from what the task-substitution framework predicts; that credible AI adopters should disproportionately displace AI-exposed workers, whereas the information channel predicts no such pattern. Using an event-study specification that traces the AI-exposure-weighted composition of the workforce around layoffs, the preliminary evidence shows that credible laying-off firms do not exhibit relative declines in AI-exposed workers and, if anything, disproportionately displace workers in low-exposure occupations. This evidence weighs directly against the task-substitution channel and supports the view that restructuring proceeds along organizational dimensions unrelated to task substitutability. It also speaks to an alternative signaling hypothesis, namely that firms lay off workers simply to signal their commitment to AI, since a commitment-signaling story would predict displacement concentrated in precisely the AI-exposed occupations that this result shows are spared. A limitation of the current evidence is that it tracks the composition of the surviving workforce and overall posting activity rather than the displaced workers themselves. This is because unchanged aggregate exposure could in principle arise if AI-exposed separations were offset by concurrent AI-exposed hiring. I therefore plan to measure the occupational composition of separations directly using worker-level transitions in the Revelio data.

Taken together, these results suggest that the informational environment in which restructuring occurs can be altered by a technological regime. In the context of Generative AI, the arrival of ChatGPT shifted the prior that investors hold about the motivation behind layoffs and allowed a broader class of healthy firms to restructure without bearing the full informational penalty. This carries an implication for how labor market dynamics during periods of general-purpose technology adoption should be read, since if technological regime shifts routinely generate waves of strategically motivated layoffs that are difficult to distinguish from distress-driven ones in real time, then the measured productivity–employment relationship during adoption periods will understate the eventual efficiency gains, because the restructuring that enables those gains occurs precisely during the pre-productivity-gain window. The framework thus offers a partial resolution of the disconnect between rising AI-attributed layoffs and modest measured productivity, in that the layoffs are a leading indicator of organizational restructuring rather than a lagging consequence of realized substitution. It is worth noting that the present evidence establishes a shift in market perception and in restructuring incidence during the ChatGPT episode. Establishing that these restructurings shed preexisting slack and create long-run value, rather than anticipating standard near-term cost savings, requires tracking realized AI adoption, pre-layoff firm health, and longer-horizon operating performance, which I pursue in ongoing work. The generalization to other general-purpose technology episodes should likewise be read as a hypothesis that the present evidence motivates

rather than establishes.

Several extensions are worth pursuing. Because the effect plausibly strengthens as the market comes to accept AI as a genuine driver of restructuring, I expect the announcement-return premium for credible firms to be amplified around subsequent major AI capability updates (e.g., advances in LLM models or the introduction of agentic AI). Moreover, the channel further implies that the stigma-reducing effect should be strongest when the prior probability of a value-destroying cut is highest, especially during downturns or periods of elevated financial stress. Lastly, allowing rival firms to treat each other's layoffs as informational events would connect the framework to the literature on information spillovers.

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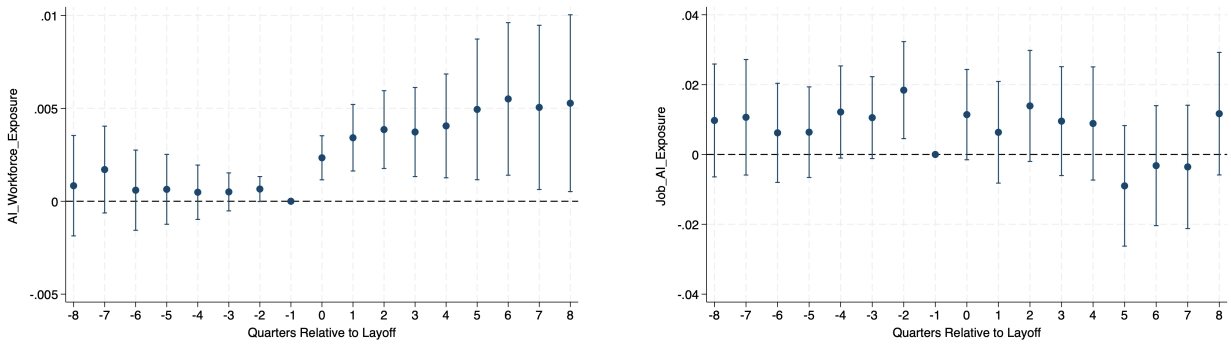
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Figure 1. Workforce AI Exposure Around Layoffs



Notes. The figure plots event-study estimates of workforce AI exposure (left panel) and AI job-posting exposure (right panel) in the quarters around a firm's first layoff in the post-ChatGPT period, estimated separately for high- and low-AI-credibility firms and normalized to the quarter before the layoff. The underlying specifications absorb firm and quarter fixed effects, and bars denote 95% confidence intervals based on standard errors clustered by firm. Because the series track the composition of the surviving workforce and overall posting activity rather than displaced workers directly, they are complemented by the planned separation-level analysis described in Section 4.

Table 1. Summary Statistics

	Mean	SD	P10	P50	P90	N
AI Exposure	0.506	0.080	0.412	0.508	0.604	3,415
AI Capital	0.002	0.019	0.000	0.000	0.003	3,891
Data Assets	0.145	0.352	0.000	0.000	1.000	2,722
Firm Size	6.918	2.827	3.396	7.178	10.247	3,880
Tobin's Q	15.625	221.688	0.958	1.532	4.740	3,799
Return on Assets	-1.181	22.361	-0.548	0.007	0.089	3,880
Book Leverage	2.099	47.525	0.033	0.272	0.674	3,878
Analyst Coverage	6.705	5.959	1.051	4.875	15.458	2,733
CAR $(-1, +1)$	-0.031	0.163	-0.162	-0.013	0.096	551

Notes. The table reports firm-level summary statistics for the sample of Compustat firms over 2020–2025, with each variable averaged to a single observation per firm. AI Exposure is the occupation-based measure of workforce exposure to AI; AI Capital is the share of a firm's employees in AI-related roles, following Babina et al. (2024); and Data Assets is constructed from data- and AI-related disclosures in 10-K filings. Firm Size is the natural log of total assets, Tobin's Q is the market-to-book ratio, and Analyst Coverage is the number of analysts issuing EPS forecasts. CAR$(-1, +1)$ is the cumulative abnormal return over the three-day window around a layoff announcement and is therefore observed only for firm-quarters that contain a layoff event, which accounts for its much smaller count. Cumulative abnormal returns are winsorized at the 1st and 99th percentiles. Sample sizes differ across rows because of differential data availability across the underlying sources (Revelio Labs, CRSP/Compustat, and LSEG I/B/E/S).

Table 2. AI Credibility and the Probability of Layoffs

	(1)	(2)	(3)	(4)	(5)	(6)
After	0.002**	0.002**	0.003***	0.003***	0.003	0.004*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
After × AI Credible	0.007***	0.007***	0.007***	0.006***	0.004**	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Credibility Measure	AI Capital		AI Exposure		Data Assets	
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	No	Yes	No	Yes	No	Yes
Industry × Quarter FE	Yes	No	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes	No	Yes
Observations	68,897	68,872	68,897	68,872	51,609	51,615
R^2	0.010	0.091	0.010	0.091	0.010	0.087

Notes. The table reports linear-probability estimates in which the dependent variable is an indicator equal to one if a firm announces a layoff in a given firm-quarter. *After* equals one from 2023 onward, that is, after the November 2022 introduction of ChatGPT. *AI Credible* indicates membership in the top pre-period quartile of the relevant credibility measure, computed over the pre-ChatGPT period and held fixed thereafter: AI Capital in columns (1)–(2), AI Exposure in columns (3)–(4), and Data Assets in columns (5)–(6). Odd columns absorb industry (SIC2) × quarter fixed effects; even columns absorb firm and quarter fixed effects, so the two designs respectively address common industry shocks and time-invariant firm heterogeneity. All specifications include lagged firm controls (size, book leverage, and cash-to-assets), with standard errors clustered by firm in parentheses. $^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table 3. AI Credibility and Layoff Announcement Returns

	(1)	(2)	(3)	(4)	(5)	(6)
After × AI Capital	0.056**	0.108***				
	(0.028)	(0.041)				
After × AI Exposure			0.017	0.073*		
			(0.043)	(0.042)		
After × Data Assets					0.068	0.053*
					(0.053)	(0.031)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	No	Yes	No	Yes	No	Yes
Industry × Quarter FE	Yes	No	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes	No	Yes
Observations	800	567	800	567	638	472
R^2	0.176	0.496	0.173	0.492	0.167	0.481

Notes. The dependent variable is the cumulative abnormal return around a layoff announcement, measured over a short event window ($\text{CAR}(-1,+1)$ in the firm-FE columns and $\text{CAR}(-1,+3)$ in the industry × quarter columns; harmonized windows will be reported in the next draft); the sample is the set of layoff events. Each pair of columns interacts *After* with one credibility measure—AI Capital in (1)–(2), AI Exposure in (3)–(4), and Data Assets in (5)–(6)—with the main effects and firm controls included but suppressed for brevity. Odd columns absorb industry × quarter fixed effects; even columns absorb firm and quarter fixed effects. Because CARs are observed only at layoff events, the firm-FE columns draw identifying variation from firms with repeated layoffs and should be interpreted as within-firm repricing among repeat announcers. Standard errors clustered by firm are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. The Opacity Channel

	(1) CAR	(2) Layoff
After × AI Credible	0.053	0.029**
	(0.036)	(0.013)
After × AI Credible × Opacity	-0.014***	-0.003***
	(0.005)	(0.001)
Firm Controls	Yes	Yes
Quarter FE	Yes	Yes
Industry × Quarter FE	Yes	Yes
Firm FE	No	No
Observations	516	8,163
R^2	0.206	0.032

Notes. The table reports the opacity refinement. *Opacity* is the dispersion of analyst EPS forecasts, measured as the forecast coefficient of variation scaled by the square root of the number of forecasting analysts, so that higher values indicate greater information asymmetry. The dependent variable is the announcement CAR in column (1) and the layoff indicator in column (2), and *AI Credible* is the AI Capital measure. All specifications include firm controls and industry × quarter fixed effects, with standard errors clustered by firm in parentheses. $^{*}\,p < 0.10$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.