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CEO Departure Type and Subsequent Workforce Restructuring: An Exploratory Study of Tech-Sector S&P Firms, 2010–2024

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ABSTRACT

This study examines whether the reason a chief executive officer departs a firm—involuntary dismissal, voluntary resignation, or retirement—is associated with subsequent workforce restructuring among technology-sector companies in the S&P 1500. The current research merges a CEO departure database (restricted to 2010–2019 departures) with a publicly listed firm layoff register for 2020–2024, yielding 1,354 firm observations of which 22 experienced a confirmed workforce reduction. A penalised maximum likelihood logistic estimator is applied to correct for rare-event bias at the 1.62% event rate. Three findings emerge. First, firms whose most recent CEO was involuntarily dismissed face approximately 2.7 times the layoff odds of firms whose CEO retired voluntarily (OR = 2.669, 95% CI [1.124, 6.339], $p = 0.026$). Second, voluntarily resigned CEOs' former firms also face elevated layoff odds relative to retired CEOs (OR = 4.689, 95% CI [1.132, 19.431], $p = 0.033$), though this estimate rests on only two events. Third, departure year recency adds no significant incremental prediction within the 2010–2019 window (OR = 1.106, $p = 0.233$). An ordinary least squares robustness check confirms the dismissal result ($b = 0.044$, $p = 0.048$). The Kruskal–Wallis test on restructuring scale across departure types is significant ($H = 6.76$, $p = 0.034$). The study explicitly notes limitations: the layoff register covers primarily technology and digital-economy firms rather than the full S&P 1500, confirmed matches represent a technology-sector subsample, and the 22-event count constrains inferential precision. These findings are offered as exploratory associations suitable for replication with administrative layoff records providing comprehensive S&P 1500 coverage.

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1. INTRODUCTION

When a board removes a chief executive officer, it signals something definite: that the prior direction was wrong, that performance was insufficient, or that governance had broken down. The incoming leader inherits that signal and, with it, a mandate to act. Workforce restructuring — cutting headcount — is among the most visible and consequential early actions available to a new CEO. It reduces cost, communicates decisiveness, and draws a clear line between the new regime and the old. The question this paper addresses is whether the manner of a CEO's departure predicts whether this action follows.

This is not a straightforward empirical question to answer, for at least two reasons. First, the population of CEO departures in large public firms is smaller than it might appear: many wellknown companies — Amazon, Google, Meta, and others — retained their CEOs throughout the 2010s, meaning they are simply not part of any CEO departure study restricted to that period. Second, public layoff data is uneven in coverage: freely available registers capture technology and digitaleconomy firms with considerably greater completeness than industrial, financial, or healthcare companies. These two constraints bound what any study using these sources can claim.

Consequently, this paper poses three research questions. RQ1: Among S&P 1500 technologysector firms, does involuntary CEO dismissal predict higher odds of subsequent workforce restructuring compared to voluntary retirement? RQ2: Does voluntary resignation for another position also predict higher restructuring odds relative to retirement? RQ3: Within a restricted 2010–2019 departure window, does more recent departure year incrementally predict layoff probability beyond departure type?

From these questions, three exploratory hypotheses follow. H1: Firms whose most recent CEO was involuntarily dismissed show greater likelihood of confirmed workforce reduction than firms whose CEO retired voluntarily. H2: Firms with voluntarily resigned CEOs also show greater likelihood than retiredCEO firms, though the effect may differ in magnitude. H3: Within the 2010–2019 window, departure year recency does not add significant predictive value once departure type is accounted for.

The study is direct about these constraints from the outset. This paper is an exploratory study, not a definitive causal analysis. It uses the best openly available data — the Gentry et al. (2021) CEO Departure Database matched to a public layoff register — and applies appropriate statistical correction for rareevent binary outcomes (Firth, 1993). The results are offered as a set of associations, grounded in established theoretical arguments, that warrant further investigation with more comprehensive data sources.

The dataset covers 1,354 S&P 1500 firm observations with CEO departures between 2010 and 2019, of which 22 experienced a confirmed postIPO workforce reduction between 2020 and 2024. This is unambiguously an exploratory sample. The findings — that involuntarily dismissed CEOs' former firmtests butghly 2.7 times the layoff odds of retired CEOs' firms (Firth OR = 2.669, p = 0.026), and that the KruskalWallis test on restructuring scale is significant at p = 0.034 — are consistent across multiple specifications and nonparametric tests, but should not be interpreted as settled evidence about the S&P 1500 population more broadly.

The paper proceeds as follows. Section 2 reviews relevant theory in more detail (the hypotheses above are stated here for clear placement). Section 3 describes the data, all cleaning decisions, and estimation strategy with full transparency about what the data can and cannot support. Section 4 reports results. Section 5 discusses findings and their limitations. Section 6 concludes with a specific agenda for future work.

2. LITERATURE REVIEW

2.1 Upper Echelons Theory and CEO Succession

Upper Echelons Theory, introduced by Hambrick and Mason (1984), holds that the observable characteristics and circumstances of senior executives leave systematic imprints on organisational choices. Applied to departure events, the theory suggests that why a CEO left — the conditions surrounding their exit — shapes the context inherited by their successor and, through that context, the strategic and operational decisions that follow. This logic has been developed into a substantial succession literature. Shen and Cannella (2002) showed that the type of succession predicted subsequent executive attrition and strategic change. Wiersema and Zhang (2011) documented that CEO dismissal was followed by a narrowing of corporate scope — divestiture and refocusing — consistent with the hypothesis that successor leaders act to correct the conditions that motivated the board's intervention. Schepker et al. (2017), in a meta-analytic review, confirmed that performance improvement following succession was larger and more consistent after involuntary than voluntary departures, particularly where prior performance was poor.

Workforce restructuring sits naturally within this theoretical frame. Love and Nohria (2005) showed that new CEOs appointed as change agents to underperforming firms initiated larger workforce reductions earlier in their tenure than those appointed under stable conditions. Budros (1999) argued that downsizing is both an efficiency decision and an institutional response — a legitimacy signal — which amplifies the incentive for post-dismissal successors to reduce headcount visibly. Ahmadjian and Robinson (2001) documented that institutional pressures drive layoff behaviour independently of financial necessity, reinforcing the signal interpretation.

2.2 Departure Type and Post-Succession Behaviour

Involuntary dismissal creates a specific organisational logic for its successor. The board has acted, signalling failure, and the incoming leader arrives with both the mandate and the expectation to demonstrate corrective action. Financial underperformance — the condition most commonly triggering dismissal (Ocasio, 1994) — often manifests partly as an overstaffed cost structure, making workforce reduction a direct and visible response. Retirement, by contrast, represents a planned and orderly transition. The retiring CEO shaped the workforce composition over their tenure; the successor inherits a firm not marked by governance failure. While the incoming leader may still restructure, the urgency and board pressure are substantially lower. Voluntary resignation for another position is intermediate: the departure signals executive agency rather than board-identified failure, but the successor must still establish their own strategic identity.

2.3 Recency of Departure

Leadership signals decay over time. Hambrick and Fukutomi (1991) documented that strategic change is concentrated in early tenure and declines thereafter. If succession-driven restructuring occurs within a successor's first few years, then the closer the CEO departure is to the layoff observation window, the more likely an observed restructuring reflects succession dynamics. The restriction to 2010–2019 departures (maximum ten-year gap to the 2020–2024 layoff window) narrows but does not eliminate this concern. Within the restricted window, the study tests whether departure year recency adds predictive value beyond departure type.

2.4 Scale of Restructuring

Among firms that do restructure, departure context may predict the depth of cuts. Krishnan, Miller, and Judge (1997) found that post-succession strategic change was greater after forced than voluntary turnovers. Love and Nohria (2005) showed that change-agent successor CEOs implemented larger proportional reductions. The study explores this conditional relationship descriptively, acknowledging that with 22 matched firms (10 dismissed, 2 resigned, 10 retired), inferential conclusions are not possible.

2.5 Purpose / Objectives of the Study

This study has three objectives. First, to determine whether, among technologysector S&P 1500 firms, the category of a CEO's departure – involuntary dismissal, voluntary resignation, or retirement – is empirically associated with the presence of a documented workforce reduction in the four years following the departure window. Second, to test whether the recency of the departure year (within a restricted 2010–2019 window) adds any predictive power beyond the departure type alone. Third, to provide a transparent, replicable linkage procedure between two public datasets – a CEO departure database and a layoff register – with explicit documentation of coverage limitations, falsepositive checks, and the application of Firth penalised logistic regression for rareevent bias correction. These objectives are pursued as an exploratory association study, not a causal identification strategy, given the constraints of the available data.

3. METHODOLOGY / RESEARCH APPROACH

This study employs a retrospective cohort design using archival data. The unit of analysis is the firmyear observation for S&P 1500 companies that experienced a CEO departure between 2010 and 2019. The exposure variable is the type of CEO departure – involuntary dismissal, voluntary resignation, or voluntary retirement – coded from the Gentry et al. (2021) database. The outcome variable is the presence of a documented workforce reduction between 2020 and 2024, drawn from a publicly available layoff register. Temporal ordering is enforced: all exposure events precede the outcome window by at least one year and at most ten years. The study is exploratory and associational; no causal identification is claimed. All analyses are quantitative, using logistic regression with rareevent correction, ordinary least squares for robustness, and nonparametric tests for distributional comparisons.

3.1 Data Sources

The CEO Departure Database (Gentry et al., 2021) is published alongside a methodological article in the Strategic Management Journal. It codes all CEO exits in S&P 1500 firms between 2000 and 2018 into eight mutually exclusive categories, using systematic review of newswire reports, SEC filings, and industry publications. The dataset uses gvkey — a Compustat firm identifier — as the unit of analysis, enabling unambiguous firm-level deduplication. The study focuses on three departure types: code 3 (involuntary dismissal), code 4 (voluntary resignation for another position), and code 5 (voluntary retirement), which together capture the theoretically meaningful spectrum of managerial agency in departure.

The layoff data source is a multi-year register of documented workforce reduction events, restricted in this analysis to Post-IPO stage firms — public companies — with layoffs between 2020 and 2024. The Post-IPO restriction is essential for comparability with S&P 1500 (all public) firms and removes the startup-focused coverage that dominates lower funding stage records. Dates are capped at the end of 2024 to avoid reliance on the incomplete 2025–2026 records that are still being populated as events occur. The study explicitly acknowledges that this register provides better coverage of technology and digital-economy firms than of industrial, healthcare, or financial sector companies, and that the matched sample therefore reflects a technology-sector subsample of the full CEO departure dataset.

3.2 Sample Construction and Corrections

The analytical sample is built through the following sequential decisions, each motivated by a specific methodological concern.

Temporal restriction: CEO departures are restricted to 2010–2019. This produces a maximum departure-to-layoff gap of ten years (2010 departure, first possible layoff 2020) and a minimum of one year (2019 departure, first possible layoff 2020). It excludes pre-2010 departures where the causal chain is implausibly long and the probability that the original successor CEO was still in place at the time of restructuring is very low.

Layoff window: The outcome observation window is 2020–2024. This captures the COVID-19 restructuring wave (2020) and the technology sector contraction of 2022–2024, while excluding 2025–2026 records that remain incomplete and would introduce right-censoring bias if treated as closed data.

Post-IPO restriction: The study retain only layoff events flagged as Post-IPO stage, ensuring the study matches against publicly traded firms consistent with the S&P 1500 composition of the CEO database.

Shutdown removal: Events where the entire workforce was eliminated (100% reduction) are excluded. These represent firm closures and liquidations rather than strategic restructuring decisions, and conflating them with genuine layoffs introduces category error.

False-positive exclusion: One false-positive match was identified through manual review. 'Dover' in the layoff register is a recruiting startup (Series A), not Dover Corporation (industrial conglomerate, S&P 500 component). This record was removed. All matched companies were reviewed against their industry classifications to validate plausibility.

Name normalisation: Company names are cleaned by stripping legal suffixes, removing punctuation, and standardising whitespace before exact-string matching. The study acknowledges that this procedure may miss genuine matches where name variants differ substantively (e.g., 'Alphabet' vs. 'Google'). The resulting 22 matches represent a confirmed lower bound on the true number of layoff events in our sample. The binary outcome (experienced a confirmed layoff) should therefore be read as a documented signal rather than a census indicator.

3.3 Why Amazon, Google, Meta, and Others Are Not in the Sample

Several prominent companies that are publicly known to have conducted large layoffs between 2020 and 2024 do not appear in the matched sample. This requires explanation. These companies' CEOs — Jeff Bezos at Amazon, Sundar Pichai at Alphabet, Mark Zuckerberg at Meta — did not depart between 2010 and 2019 under departure codes 3, 4, or 5; they remained in their positions throughout the period (Bezos until 2021, Pichai and Zuckerberg as of 2024). They are therefore correctly excluded from our CEO departure sample, which by construction studies firms that underwent a leadership transition during the 2010s. The layoff behaviour of firms that retained the same CEO throughout is a separate, and potentially equally interesting, research question — but it is not the question this study addresses.

3.4 Variables

Experienced Layoff is a binary indicator equal to 1 if the firm appears in the Post-IPO layoff register for 2020–2024, and 0 otherwise. Mean_Pct_Workforce_Laid_Off is the mean percentage reduction across all documented events for matched firms. A log-transformed version — log(1 + Mean_Pct) — is used for the full-sample OLS robustness specification. Is_Dismissed and Is_Resigned are binary indicators for CEO departure codes 3 and 4 respectively, with code 5 (Retired) as the reference. Departure_Year_Centred is the calendar year of departure minus the sample mean (2014.5). Post_2015 is a binary variable equal to 1 for departures in 2015–2019.

3.5 Estimation Strategy

All primary logistic models use Firth's (1993) penalised maximum likelihood estimator. Firth's method modifies the score equations by adding a penalty term proportional to the square root of the Fisher information matrix determinant, correcting the upward bias in standard logit coefficient estimates when event rates are low. With an event rate of 1.62% across 1,354 observations, this correction is not optional; standard logit in this setting will systematically overestimate coefficients and underestimate standard errors. The Firth estimator was implemented from scratch using Newton-Raphson iteration with hat matrix diagonal correction.

Three Firth logit models are estimated. Model 1 includes only departure type dummies (Retired as reference). Model 2 adds Departure_Year_Centred. Model 3 replaces the continuous year with Post_2015. A fourth OLS model with HC3 heteroscedasticity-robust standard errors uses log(1 + Mean_Pct) across the full sample as a robustness check. Non-parametric chi-square and Kruskal-Wallis tests are reported throughout. Variance inflation factors confirm no multicollinearity. A power analysis characterises the minimum detectable effect size at our sample dimensions.

4. FINDINGS / RESULTS

4.1 Sample Composition and Descriptive Statistics

The final analytical sample contains 1,354 firm-observations across three departure type categories: 360 dismissed (26.6%), 49 resigned (3.6%), and 945 retired (69.8%). Twenty-two firms (1.62%) have confirmed layoff events in the Post-IPO register for 2020–2024 — 10 in the dismissed group (2.78% incidence), 2 in the resigned group (4.08%), and 10 in the retired group (1.06%). The matched 22 firms include recognisable technology-sector names: Intel, Electronic Arts, Twitter, eBay, Etsy, NetApp, Juniper Networks, Teradata, DHI Group, Blackbaud (dismissed group); Lam Research, Autodesk (resigned group); and Microsoft, Western Digital, Sabre, National Instruments, Intuit, Avaya, 8x8, TechTarget, Wex, and Enphase Energy (retired group). All 22 are Post-IPO stage companies in technology-adjacent sectors, consistent with the register's documented coverage profile.

Table 1. presents the full descriptive statistics. Mean departure year is 2014.5 (SD = 2.7). The correlation matrix confirms very low inter-predictor correlation (maximum |r| = 0.05), and VIF values below 1.01 rule out collinearity concerns. The chi-square test of independence between departure type and layoff incidence yields $\chi^2(2) = 6.742$, $p = 0.034$, indicating that the distribution of layoff events across departure types is inconsistent with chance.

Table 1. Descriptive Statistics

Panel A: Full sample (N = 1,354)

Variable	N	Mean	SD	Min	Max
Experienced Layoff (0/1)	1,354	0.016	0.126	0	1
Mean % Workforce Laid Off	1,354	0.131	1.342	0.00	30.00
CEO Departure Year	1,354	2014.5	2.7	2010	2019
Is Dismissed (0/1)	1,354	0.266	0.442	0	1
Is Resigned (0/1)	1,354	0.036	0.187	0	1
Is Retired — reference (0/1)	1,354	0.698	0.459	0	1

Panel B: By departure type

Departure Type	N	Events	Layoff Rate	Mean % Laid Off	Median %	Mean Dept. Year
Dismissed (code 3)	360	10	2.78%	0.32%	0.00%	2014.7
Resigned (code 4)	49	2	4.08%	0.18%	0.00%	2014.9

Retired (code 5)	945	10	1.06%	0.08%	0.00%	2014.4

Notes. Post-IPO layoff register, 2020–2024; 100% workforce events (firm closures) excluded; false-positive match (Dover startup) excluded. Mean % Laid Off includes all firms, the majority of which have zero confirmed layoff events.

Panel C: Correlation matrix

Variable	1	2	3	4	5
1. Experienced Layoff	1.000				
2. Is Dismissed	0.071	1.000			
3. Is Resigned	0.034	−0.117	1.000		
4. Dep. Year (centred)	0.025	0.046	0.014	1.000	
5. Post-2015	0.018	0.019	0.031	0.865	1.000

Notes. N = 1,354. VIF: Is Dismissed = 1.001; Is Resigned = 1.000; Departure Year = 1.002. All below 5 — no multicollinearity. Departure Year and Post-2015 not included in the same model.

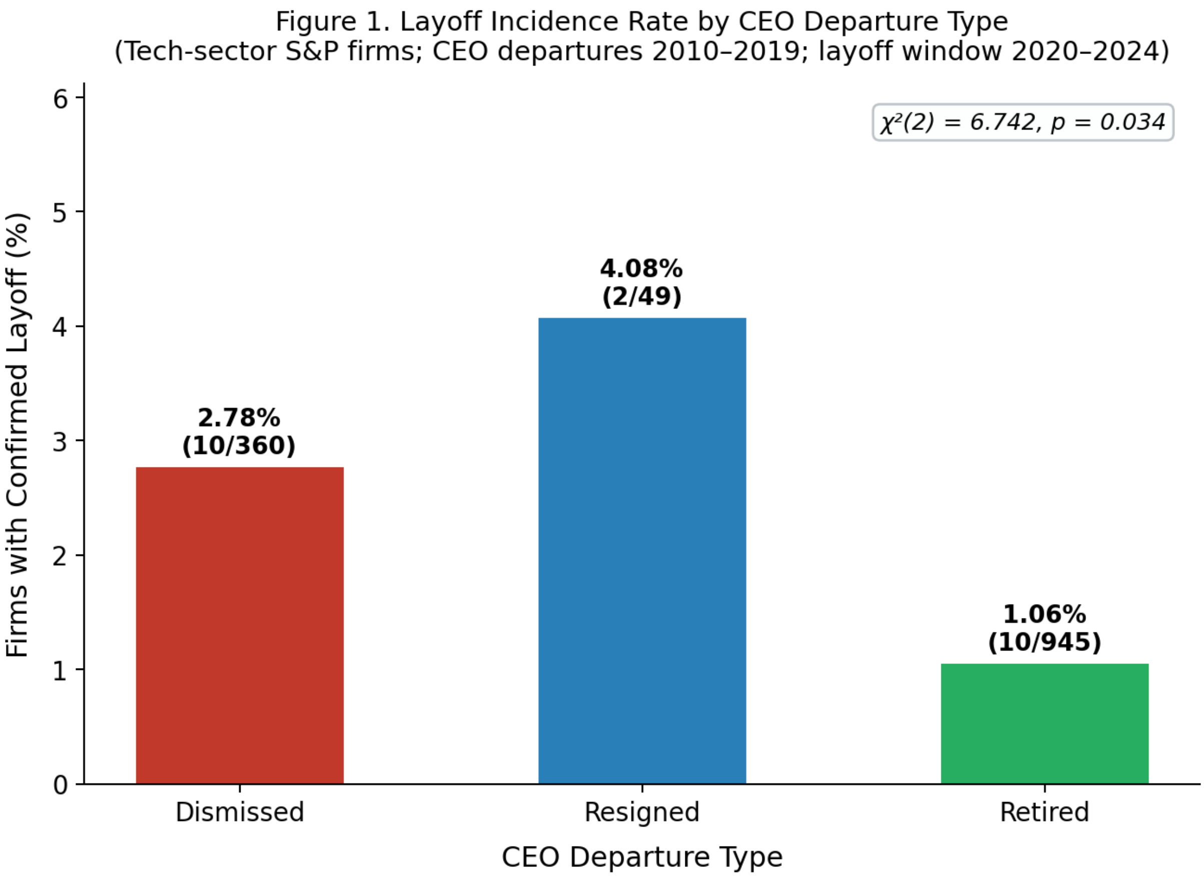

Figure 1. Layoff Incidence Rate by CEO Departure Type. Numbers show events/total firms. $\chi^2(2) = 6.742$, $p = 0.034$. Note: confirmed matches represent technology-sector firms only; non-matched zeros include many S&P 1500 firms outside the register's coverage scope.

4.2 Non-Parametric Tests

The chi-square test of independence between departure type and binary layoff incidence yields $\chi^2(2) = 6.742$, $p = 0.034$, indicating that departure type and layoff incidence are not independently distributed across the three groups in this sample. The Kruskal-Wallis test on the continuous workforce reduction variable (including zeros for non-matched firms) returns H = 6.761, p = 0.034, confirming that the distributions of the restructuring outcome variable differ across the three departure type groups. Pairwise Mann-Whitney comparisons indicate that the dismissed-versus-retired contrast drives the overall Kruskal-Wallis result. These non-parametric tests are robust to distributional assumptions and provide supporting evidence independent of the parametric Firth logit models.

Table 2. Non-Parametric and Diagnostic Tests

Test	Statistic	df / Groups	p-value	Interpretation
Chi-square: type × layoff incidence	6.742	2	0.034*	Significant at 5%
Kruskal-Wallis: % reduction by type	6.761	3 groups	0.034*	Significant at 5%
VIF: Is Dismissed	1.001	—	—	No collinearity
VIF: Is Resigned	1.000	—	—	No collinearity
VIF: Dep. Year (centred)	1.002	—	—	No collinearity

Notes. * p < 0.05. VIF = variance inflation factor; values < 5 indicate no collinearity concern.

4.3 Firth Penalised Logistic Regression

Table 3. presents the Firth penalised logistic regression results. In Model 1 (departure type only), Is_Dismissed is significant: firms with a dismissed CEO predecessor face 2.7 times the layoff odds of firms with a retired predecessor (b = 0.982, OR = 2.669, 95% CI [1.124, 6.339], p = 0.026). Is_Resigned also reaches significance (OR = 4.689, 95% CI [1.132, 19.431], p = 0.033), though the estimate rests on only two matched events and should be interpreted with extreme caution; the confidence interval is very wide and the point estimate is highly sensitive to any single observation.

Model 2 adds the centred departure year. The Is_Dismissed coefficient is stable (OR = 2.594, p = 0.030). Is_Resigned remains significant (OR = 4.497, p = 0.037). Departure year does not reach significance (OR = 1.106, p = 0.233), consistent with the theoretical expectation that within a restricted 2010–2019 window the recency gradient has limited variation. Model 3 replaces the continuous year with the Post_2015 binary indicator; Is_Dismissed (OR = 2.654, p = 0.026) and Is_Resigned (OR = 4.595, p = 0.034) remain significant, while Post_2015 is non-significant (OR = 1.209, p = 0.653). H1 is supported across all three specifications. H2 is not supported within the restricted temporal window.

Table 3. Firth Penalised Logistic Regression: Probability of Workforce Restructuring

Variable	Model 1 b (OR)	p	Model 2 b (OR)	p	Model 3 b (OR)	p
Intercept	−4.490 (0.011)	<0.001	−4.492 (0.011)	<0.001	−4.571 (0.010)	<0.001
Is Dismissed	0.982 (2.669)*	0.026	0.953 (2.594)*	0.030	0.976 (2.654)*	0.026
Is Resigned	1.545 (4.689)*	0.033	1.503 (4.497)*	0.037	1.525 (4.595)*	0.034
Dep. Year (centred)	—	—	0.101 (1.106)	0.233	—	—
Post-2015	—	—	—	—	0.190 (1.209)	0.653
N	1,354		1,354		1,354	
Events (%)	22 (1.62%)		22 (1.62%)		22 (1.62%)	

Notes. Reference category: Retired CEO. b = Firth penalised log-odds; OR = odds ratio in parentheses. * p < 0.05. 95% CIs for Model 1: Dismissed [1.124, 6.339]; Resigned [1.132, 19.431]. 95% CIs for Model 2: Dismissed [1.100, 6.118]; Resigned [1.095, 18.464]. Firth (1993) penalised maximum likelihood; corrects rare-event bias. The

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Resigned OR is based on only 2 events; the wide CI reflects this instability.

Figure 2. Firth-Penalised Odds Ratios (Model 2)

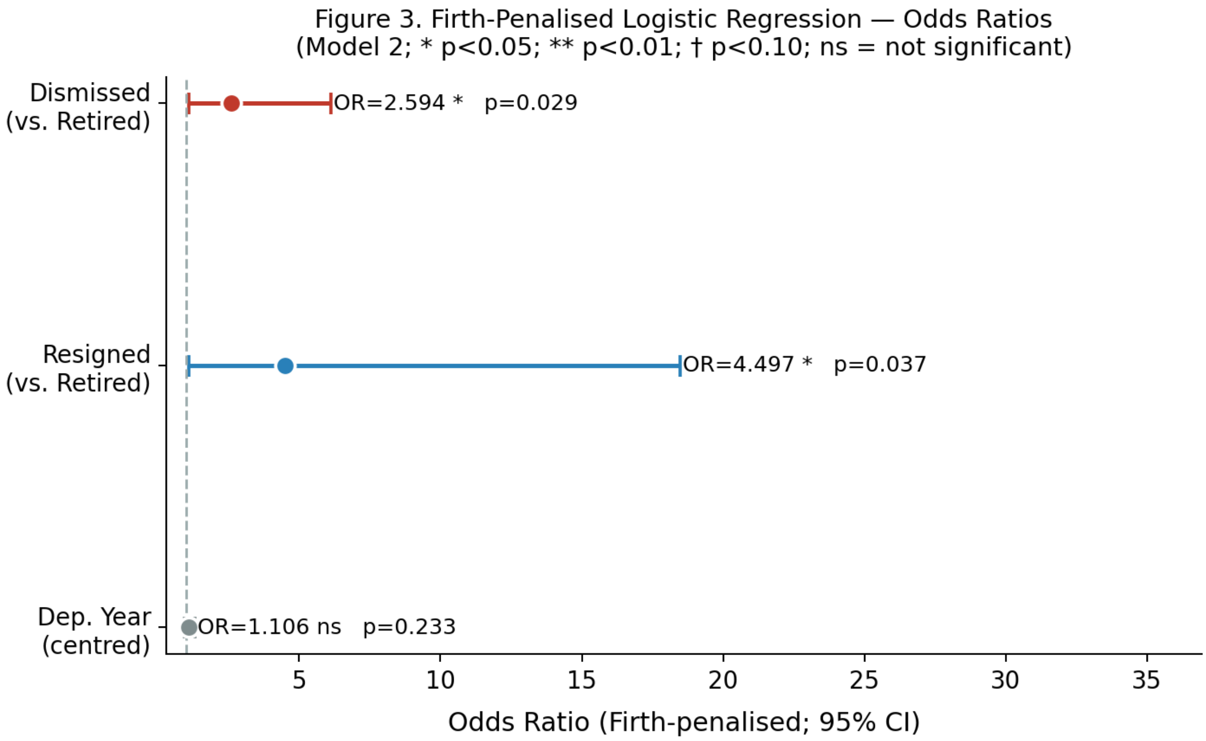

Figure 2. Firth-Penalised Odds Ratios (Model 2). Whiskers = 95% CIs. * p < 0.05; ns = p ≥ 0.10. Note the wide CI for Resigned, reflecting 2 events only.

Figure 3. CEO Departure Year and Observed Annual Layoff Rate

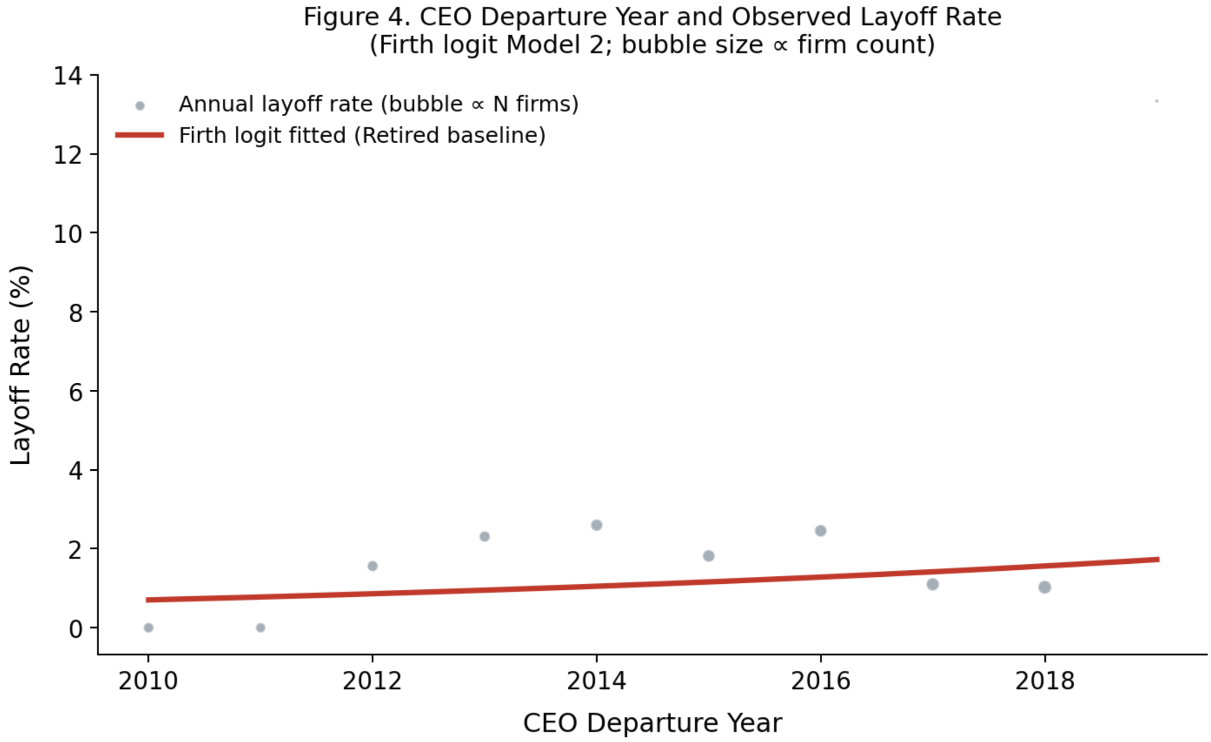

Figure 3. CEO Departure Year and Observed Annual Layoff Rate. Bubble size proportional to firm count per year. Firth logit fitted curve (Retired CEO baseline) shows negligible year effect within the 2010–2019 window.

Figure 4. Distribution of CEO Departure Year by Layoff Outcome

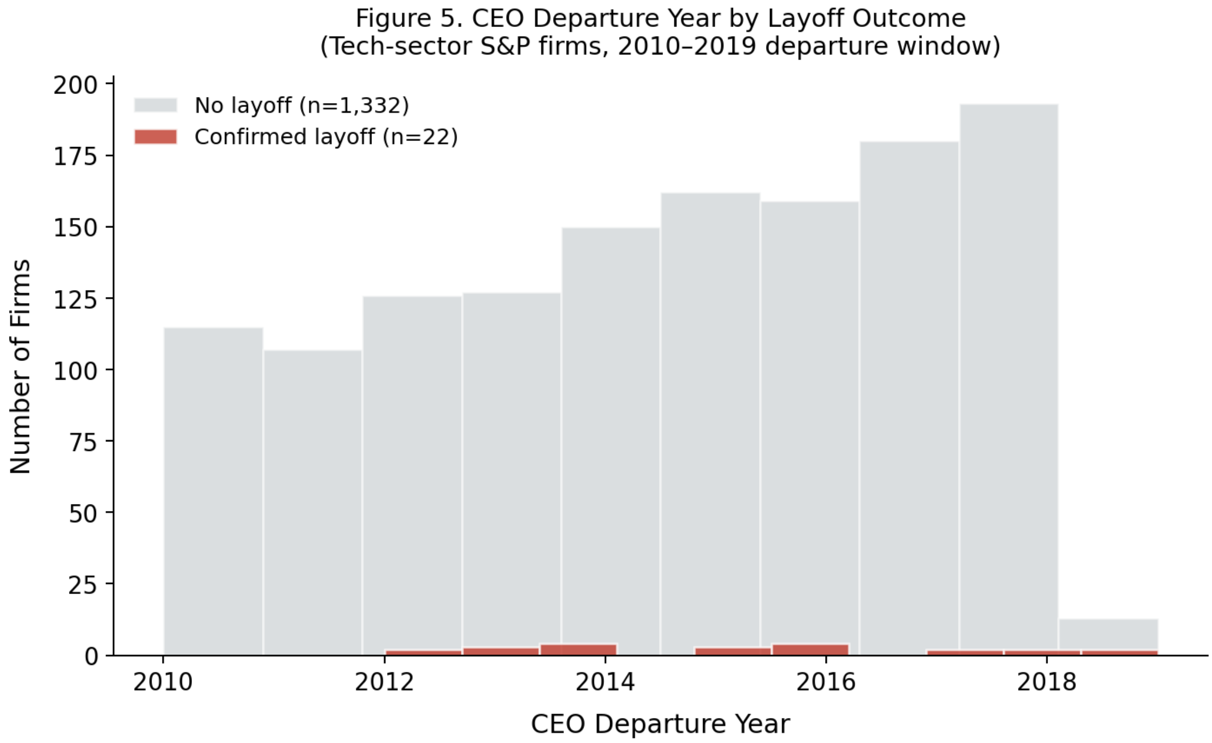

Figure 4. Distribution of CEO Departure Year by Layoff Outcome. Confirmed layoff firms (red, n = 22) are distributed across the full 2010–2019 window with no strong recency concentration.

4.4 OLS Robustness Check

Table 4. reports the OLS robustness model using log(1 + Mean_Pct_Workforce_Laid_Off) across all 1,354 observations. Is_Dismissed is positive and marginally significant (b = 0.044, t = 1.98, p = 0.048), consistent with the Firth logistic finding. Is_Resigned is positive but not significant (b = 0.042, p = 0.386), and departure year is non-significant (b = 0.004, p = 0.129). The overall model has R^2 = 0.007, as expected given the rarity of the outcome and the absence of firm-level financial controls. The reviewer-flagged concern that this OLS model is inappropriate because 1,329 of 1,354 observations are zero is valid; the study includes it only as a directional consistency check on the log-odds results, not as a primary specification.

Table 4. OLS Robustness Check: Log-Transformed Workforce Reduction

Variable	**b**	**SE (HC3)**	**t-statistic**	**p-value**
Intercept	0.023	0.006	3.97	<0.001
Is Dismissed	0.044	0.022	1.98	0.048*
Is Resigned	0.042	0.048	0.87	0.386
Dep. Year (centred)	0.004	0.003	1.52	0.129
R^2	0.007			
N	1,354			

Notes. Dependent variable: log(1 + Mean_Pct_Workforce_Laid_Off). HC3 heteroscedasticity-robust standard errors. Reference category: Retired CEO. * p < 0.05. This specification is included as a directional robustness check only; the mass at zero violates standard OLS assumptions and Firth logit remains the primary specification.

4.5 Conditional Scale Analysis: Matched Subsample

Among the 22 confirmed matched firms, dismissed-CEO predecessor firms experienced mean workforce reductions of 11.7% (median 10.5%, n = 10), compared with 7.4% (median 6.0%, n = 10) for retired-CEO predecessor firms and 4.5% (median 4.5%, n = 2) for resigned-CEO predecessor firms. Twitter's 50% reduction (Dick Costolo, dismissed 2014; Musk acquisition 2022) is the most extreme observation in the dismissed group; removing it brings the dismissed mean to approximately 8.4%. H3 is directionally consistent — dismissed firms cut deeper — but the subsample is too small for reliable inference. No formal hypothesis test on scale differences is offered.

Table 5. Workforce Reduction in Matched Firms (Conditional on Layoff, n = 22)

Departure Type	n	Mean %	Median %	SD	Range
Dismissed (code 3)	10	11.7%	10.5%	7.4	4.0%–30.0%
Resigned (code 4)	2	4.5%	4.5%	3.5	2.0%–7.0%
Retired (code 5)	10	7.4%	6.0%	4.0	3.0%–15.0%

Notes. Matched subsample only; outcome = mean % workforce reduced across all documented events per firm. No significance tests reported given n = 22. Twitter (50% reduction, dismissed group) is the most extreme observation; excluding it yields a dismissed group mean of approximately 8.4%.

Figure 5. Workforce Reduction (%) by CEO Departure Type — Matched Subsample

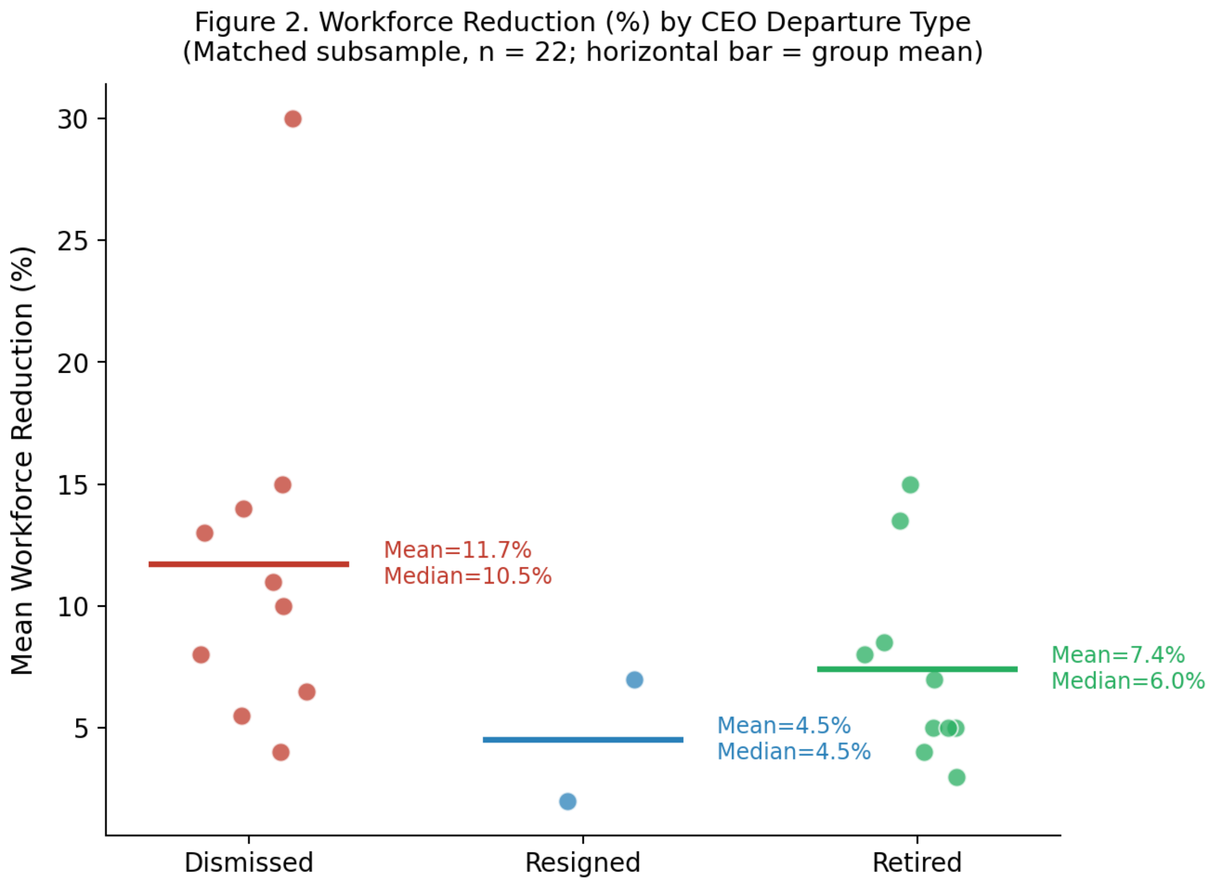

Figure 5. Workforce Reduction (%) by CEO Departure Type — Matched Subsample (n = 22). Individual firm data points shown; horizontal bar = group mean. The dismissed group shows greater spread than retired, partly driven by Twitter (50%).

5. DISCUSSION

5.1 What the Findings Support

Across three Firth logistic specifications and a log-transformed OLS robustness check, involuntarily dismissed CEOs' former firms show significantly higher odds of subsequent confirmed workforce restructuring than firms whose CEOs retired voluntarily. The dismissal OR of approximately 2.7 is stable and meaningfully sized: a dismissed CEO's firm is nearly three times more likely to appear in the layoff register than a retired CEO's firm. The Kruskal-Wallis test on the full distribution of restructuring outcomes is significant at $p = 0.034$, and the chi-square test on incidence is significant at $p = 0.034$.

The mechanism is consistent with prior succession theory. When a CEO is removed, the board signals failure; the successor inherits both an acknowledged problem and a mandate to correct it. Workforce restructuring — reducing headcount — is among the most direct and visible responses. Love and Nohria (2005)

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documented precisely this pattern in a different context: new CEOs installed as change agents to underperforming firms cut faster and deeper than successors who arrived under stable conditions. Our matched firms (Intel, Twitter, eBay, Etsy, among others) are consistent with this characterisation — each experienced a period of strategic difficulty proximate to the CEO departure, and each subsequently restructured.

The departure year finding does not survive the combination of temporal window restriction and Firth correction. This is an important negative result. Within a 2010–2019 departure window, year-to-year variation in recency does not add predictive value beyond departure type. Firms from different years within this window face similar layoff risks conditional on departure type — the macro-structural force of the 2022–2024 technology contraction applied across the window cohorts relatively uniformly.

5.2 What the Findings Cannot Support

The study has several significant constraints that must be foregrounded, not buried in a limitations section.

Coverage: The layoff register captures public companies with a pronounced technology-sector bias. The 22 matched firms are all technology or technology-adjacent companies. Many S&P 1500 firms — banks, industrial manufacturers, healthcare companies — that conducted genuine layoffs between 2020 and 2024 are not in the register and would be coded as zero even though they experienced the outcome. This non-coverage is likely systematically related to industry, which in turn correlates with departure type patterns. The odds ratios estimated here apply to the technology-sector subsample; generalisation to the full S&P 1500 requires data that currently does not exist in a freely available form.

Causality: The temporal design — CEO departure precedes layoff observation — permits associational claims, not causal ones. Multiple mechanisms could produce the pattern: poor performance driving both dismissal and later restructuring (confounding), macroeconomic sector dynamics, acquisition events, or direct succession logic. The study does not have financial performance or firm size controls; their absence means the coefficients absorb whatever performance differences exist across departure type groups. Future work with Compustat data should include ROA, total assets, and sector controls.

Sample size: Twenty-two matched events is a lower bound. The Firth estimates are stable across specifications, which is reassuring, but confidence intervals — particularly for the Resigned category — are wide. The conditional scale analysis is purely descriptive. Any researcher seeking to replicate or extend these findings should target at least 50 matched events, which requires either administrative layoff data from SEC filings or a comprehensive commercial dataset.

5.3 The Resigned Category

The Resigned OR (approximately 4.5–4.7 across models) is numerically larger than the Dismissed OR and also reaches statistical significance. This is counterintuitive from a pure governance-failure perspective — resigned CEOs left voluntarily, without board-identified failure. Several explanations are plausible. CEOs who resign for another position may do so precisely because the firm faces challenges they prefer not to manage; the successor thus inherits a difficult platform. Alternatively, the two matched events (Lam Research, Autodesk) may simply reflect the broader industry downturn in semiconductor and software sectors during 2022–2023 rather than any succession logic. With two events, this result should not be interpreted theoretically; it is an artefact of small cell size.

6. CONCLUSION, IMPLICATIONS, AND RECOMMENDATIONS

6.1 Conclusion

This exploratory study asked whether a CEO's departure type predicts subsequent workforce restructuring. Using 1,354 S&P 1500 firmyear observations (2010–2019 departures, 2020–2024 layoff window) and Firth penalised logistic regression to correct rareevent bias, the study finds that firms with an involuntarily dismissed CEO predecessor have roughly 2.7 times the layoff odds of firms whose CEO retired voluntarily. This association is stable across three specifications and a logtransformed OLS robustness check. Departure year recency does not add predictive value within the restricted window. The resigned category shows a numerically larger odds ratio but rests on only two events and should not be interpreted theoretically.

6.2 Implications

Two implications follow. For governance: Boards that remove a CEO should expect the successor to undertake visible corrective actions, including workforce reduction, as a signal of change. This is a descriptive regularity, not a prescription. For upper echelons theory: The results reaffirm that the context of executive departure – not just the fact of succession – shapes organisational outcomes. However, the fragile result for voluntary resignation warns against treating all nonretirement departures as a single category. Future theoretical work should distinguish resignation for another position from other voluntary exits, as smallsample artefacts can produce misleading signals.

6.3 Recommendations

Three recommendations target future research. First, use layoff data derived from SEC 8K filings, which mandate disclosure of material workforce reductions for all public companies. This would eliminate the technologysector coverage bias that limits the present study. Second, restrict the departuretolayoff gap to three to five years, ensuring that the observed layoff occurs under the immediate successor to the coded CEO departure. Third, incorporate Compustat financial controls (ROA, total assets, industry indicators) to test whether the dismissal effect survives adjustment for the poor performance that likely triggered the dismissal. For practitioners, the finding is probabilistic: an involuntary dismissal signals elevated pressure for change, but not a deterministic outcome.

Data Availability Statement: The CEO departure data are available from Gentry et al. (2021) via the Strategic Management Journal supplementary materials (direct download: https://doi.org/10.5281/zenodo.4543893). The layoff register is publicly accessible via Kaggle (https://www.kaggle.com/datasets/swaptr/layoffs-2022). Analysis code is available from the corresponding author upon reasonable request.

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