The Impact of Spinoffs on the Information Environment of Peer Firms: Information Spillovers or Industry Disruption

by

Jonathan Yuan

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Examining Committee Membership

The following served on the Examining Committee for this thesis. The decision of the Examining Committee is by majority vote.

External Examiner	NAME: Wuyang Zhao Title: Associate Professor
Supervisor(s)	NAME: Changling Chen Title: Associate Professor
Supervisor(s)	NAME: Haihao Lu Title: Associate Professor
Internal Member	NAME: Alan Douglas Title: Associate Professor
Internal Member	NAME: Steve Fortin Title: Professor
Internal-external Member	NAME: Jean Guillaume Forand Title: Associate Professor

Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Spinoffs are a form of divestiture in which a parent firm separates a portion of its operations into a newly created and independent spinoff firm. This thesis examines how spinoffs affect the information environment of the parent firm's peers using a sample of U.S. spinoffs from 2010 to 2018. I find that analyst forecast dispersion decreases for peers after a cross-industry spinoff. This result is more pronounced when the parent firm is operationally complex prior to the spinoff, suggesting that the separation of unrelated operations can reduce analysts' information processing costs and facilitate information spillovers between peers. Conversely, I find that forecast accuracy decreases and forecast dispersion increases for peers after a same-industry spinoff. These results are more pronounced for peers that operate in industries that become less concentrated and peers that experience more volatile cash flows and income in the post-spinoff period. Together, these results suggest that same-industry spinoffs can be disruptive industry events that change industry compositions and outweigh the potential informational benefits of the spinoff firm's initial financial statements, thereby complicating the forecasting process for analysts. Overall, this thesis identifies new mechanisms that helps explain the spillover effects of spinoffs on the information environment of the parent firm's peers and demonstrates that the operational similarity between the parent and spinoff firms is an important determinant of these effects.

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Table of Contents

List of Figures

List of Tables

Chapter 1: Introduction

Industry composition constantly changes as firms adjust their market positions in response to shifting incentives. Firms may choose to enter or exit an industry or adjust the scope of their operations through mergers and acquisitions (M&As) and divestitures. While these corporate restructurings have direct implications on the firms that undertake them, an emerging stream of literature recognizes that corporate restructurings such as M&As, going-private transactions and spinoffs, are industry-wide events that have spillover effects on the information environment of industry peers (Sheen 2014; Kim and Suh 2023; Brown, Byard, Darrough, and Suh 2024; Hinson and Piao 2025; Kim, Kim, Rosano, and Suh 2025).

This thesis examines the spillover effects of spinoffs on the information environment of the parent firm's close peers. Spinoffs are a form of divestiture in which a parent firm separates a portion of its operations into a newly created and independent spinoff firm. In recent years, spinoffs have become more prevalent and economically significant. The global market value of spinoffs reached $203 billion in 2021, underscoring their importance in increasing corporate focus and maximizing shareholder value (WLRK 2022; Rouleau 2023).[1] Moreover, from 1980 to 2017, the average parent firm divested $1.7 billion or 25% of its market capitalization (Chen, Lin and Lin 2024). Recent studies that examine the spillover effects of spinoffs focus on the informational benefits of the spinoff firm's initial financial statements on its close peers, as the newly created spinoff firm is required to file its own set of financial statements (Kim and Suh 2023; Kim, Kim, Rosano and Suh 2025). This thesis extends prior literature by (1) examining the spillover effects

[1] Notable spinoff announcements include General Electric in 2021 and Kellogg's in 2022.

of spinoffs on the parent firm's close peers and (2) distinguishing between cross-industry and same-industry spinoffs when identifying the mechanisms that explains these effects.

Cross-industry spinoffs occur when the pre-parent firm separates its unrelated operations, resulting in post-parent and spinoff firms that operate in unrelated industries.[2] Cross-industry spinoffs may facilitate information spillovers by reducing analysts' information processing costs. Sell-side analysts possess industry expertise (Boni and Womack 2006; De Franco, Hope, and Larocque 2015) and incorporate information from multiple industry peers when forecasting earnings (Ramnath 2002; Bradshaw, Miller, and Serafeim 2009; De Franco, Kothari, and Verdi 2011; Brown, Byard, Darrough and Suh 2024; Hinson and Piao 2025). Analysts who follow a diversified firm may incur higher information processing costs as these firms are more complex and the analysts' expertise may be limited to certain segments (Baik, Johnson, Kim, and Yu 2023). If the pre-parent firm separates its unrelated operations through a cross-industry spinoff, the post-parent firm may be less costly for analysts to follow as the remaining operations of the post-parent firm is more aligned with analysts' industry expertise. Therefore, cross-industry spinoffs could reduce analysts' information processing costs and facilitate information spillovers between the parent firm and its close peers, leading to higher forecast accuracy and lower forecast dispersion.

In contrast, same-industry spinoffs occur when the post-parent and spinoff firms operate in the same or related industries.[3] Ex-ante, it is unclear how same-industry spinoffs affect the forecast accuracy and forecast dispersion of the parent firm's close peers. Same-industry spinoffs can increase the quantity and quality of public information as the newly created spinoff firm files its initial set of financial statements. These financial statements can provide incremental information

[2] The pre-parent firm refers to the parent firm before the spinoff effective date. The post-parent firm refers to the parent firm after the spinoff effective date.
[3] This also suggests that the post-parent and the spinoff firms share the same set of close peers.

about the close peers' industry as financial information about the spinoff firm in the pre-spinoff period is limited to segment disclosures by the pre-parent firm. Since industry peers have positively correlated firm fundamentals and act as information complements (Banerjee, Dasgupta, Shi, and Yan 2023), incremental public information from the spinoff firm's initial financial statements may expand the analysts' information set and lead to higher forecast accuracy and lower forecast dispersion for the parent firm's close peers. However, same-industry spinoffs may also serve as disruptive industry events as the contraction of the parent firm and the introduction of the spinoff firm as a stand-alone competitor can change the industry composition. Forecasting earnings may be more difficult for the parent firm's close peers as analysts need to evaluate the impact of changing industry composition on peer firm's earnings. As a result, the heightened difficulty can lead to lower forecast accuracy and higher forecast dispersion for the parent firm's close peers (Gaspar and Massa 2006; Datta, Iskandar-Datta and Sharma 2011; Haw, Hu and Less 2015). Given the opposing effects of increased disclosure and changes in industry composition, the overall impact of same-industry spinoffs on the analyst forecast properties of the parent firm's close peers is an empirical question.

Data on U.S. spinoffs are obtained from Form 10-12B filings in SEC EDGAR. These filings are required for firms that seek to issue new stock through a spinoff. The sample period spans from 2010 to 2018 to avoid confounding effects from the 2008 financial crisis and 2020 COVID pandemic. Each spinoff is a standalone event and not associated with concurrent M&As and bankruptcies. To ensure that the sample of spinoffs have financial statement consequences, the pre-parent and post-parent firms must provide financial reports before and after the spinoff effective date, respectively, while the spinoff firm must provide financial reports afterwards. In addition, within each spinoff, the parent firm must have at least one close industry peer and one distant industry peer. Close peers serve as the treatment group as these firms are most affected by the spinoff. Distant peers, rather than non-industry peers, serve as the control group as they are less affected by the spinoff while still maintaining comparable characteristics with close peers (Beatty, Liao, and Yu 2013; Banerjee, Dasgupta, Shi and Yan 2023).[4] The final sample consists of 76 spinoffs.

In the first set of analyses, this thesis uses a difference-in-difference research design to examine the impact of cross-industry and same-industry spinoffs on the forecast accuracy of the parent firm's close peers, relative to its distant peers, between a six-quarter period ending before the initial filing date of the Form 10-12B (i.e., the pre-spinoff period) and a six-quarter period starting after the initial financial report by the post-parent firm after the spinoff effective date (i.e., the post-spinoff period). The regression is estimated at the spinoff-peer firm-analyst-quarter level and controls for forecast, analyst, brokerage, peer firm and industry characteristics. The regression also includes fixed effects for each spinoff event, firm × event, analyst × event and quarter-cohort, with clustered standard errors at the peer firm level. The sample consists of 1,107 close peers, 3,928 distant peers, and a total of 183,393 observations.

In the second set of analyses, this thesis uses a difference-in-difference research design to examine the impact of cross-industry and same-industry spinoffs on the forecast dispersion of close peers, relative to distant peers, across the pre-spinoff and post-spinoff periods. The regression is estimated at the spinoff-peer firm-quarter level and differs from the previous analysis by excluding controls for forecast, analyst and brokerage characteristics and analyst × event fixed effects. The sample consists of 290 close peers, 1,863 distant peers, and a total of 23,778 observations.

[4] Consistent with prior studies, this thesis uses industry classification codes to define close and distant peer firms (Beatty, Liao, and Yu 2013; Banerjee, Dasgupta, Shi, and Yan 2023).

In the main results, I find that forecast dispersion decreases for close peers, relative to distant peers, after a cross-industry spinoff. The result is more pronounced when the pre-parent firm is operationally complex, measured by the number of reportable segments disclosed in the latest financial report in the pre-spinoff period. These results suggest that the separation of unrelated operations is more effective at reducing analysts' information processing costs for operationally complex firms, thereby facilitating information spillovers between the parent firm and its close peers.

In contrast, I find that forecast accuracy decreases and forecast dispersion increases for close peers, relative to distant peers, after a same-industry spinoff. These results suggest that same-industry spinoffs can be disruptive industry events, as the increase in uncertainty outweighs the informational benefits of the spinoff firm's initial financial statements. To identify the underlying mechanisms, I perform a series of cross-sectional analyses. First, I find that the results are more pronounced for peers that operate in industries that becomes less concentrated and peers that experience more volatile cash flows and income after a same-industry spinoff. These results suggest that same-industry spinoffs that lead to more competitive environments and volatile peer firm fundamentals can complicate the forecasting process for analysts. Second, using hand-collected segment disclosure data, I find that the results are less pronounced if the spinoff firm provides incremental segment disclosures in the post-spinoff period, suggesting that these disclosures are informative to analysts and help them navigate changes in industry composition. Overall, the main results of this thesis demonstrates the importance of distinguishing between cross-industry and same-industry spinoffs when examining the spillover effects of spinoffs on the analyst forecast properties of the parent firm's close peers.

Next, I examine whether the main results are moderated by the level of information uncertainty in the peer firm's information environment in the pre-spinoff period. Analysts forecast properties for peer firms may be less affected if the peer firm has a strong information environment in the pre-spinoff period. Information uncertainty is measured as the peer firm's average daily bid-ask spread for 180 days ending on the quarter before the initial filing date of the Form 10-12B. After a cross-industry spinoff, I find that the decrease in forecast dispersion is more pronounced for close peers, relative to distant peers, with higher information uncertainty in the pre-spinoff period. This finding suggests that the decrease in analysts' processing costs is particularly beneficial for analysts who follow peer firms with weaker information environments. Conversely, after a same-industry spinoff, I find that the decrease in forecast accuracy and increase in forecast dispersion is less pronounced for close peers, relative to distant peers, with lower information uncertainty in the pre-spinoff period. This finding suggests that analysts who follow peer firms with stronger information environments are more resilient to disruptions arising from changes in industry composition.

Finally, I perform several tests to assess the robustness of the main results. First, I assess the parallel trends assumption and find that close and distant peers exhibit similar trends in analyst forecast properties in the pre-spinoff period. Second, I use entropy balancing to reweight distant peers such that the weighted means, variances and skewness of the covariates are balanced with those of close peers. The results remain consistent for cross-industry spinoffs but are weaker for same-industry spinoffs. The attenuation may be a result of the smaller number of close peers than distant peers, which could cause the reweighting process to assign disproportionally large weights to a small subset of comparable distant peers and small weights to the remaining control sample. Third, I assess the pervasiveness of the spillover effects by using alternative definitions of close and distant peers based on SIC codes. In the main analysis, peer firms that share the same three-digit SIC code, but different four-digit SIC code as the pre-parent firm are excluded from the sample to distinguish between close and distant peers. I find consistent results when I broaden the definition of distant peers by including these previously excluded peer firms, but I find weaker results when I broaden the definition of close peers. These results suggest that the spillover effects of spinoffs are concentrated within close peers as the previously excluded peer firms behave more similarly to distant peers. Finally, I replicate the main analyses by defining close and distant peers with North American Industry Classification System (NAICS) codes. The results for same-industry spinoffs are robust but I observe weaker results for cross-industry spinoffs.

This thesis provides several potential contributions. The spinoff literature has primarily focused on the direct effects of spinoffs on the parent and spinoff firms. Prior research has examined the direct effects of spinoffs on shareholder wealth, bondholder wealth, operating efficiency, investment efficiency, and the information environment.[5] More recently, studies have begun to examine the spillover effects of spinoffs on the spinoff firm's peers. Kim and Suh (2023) find that the incremental disclosures from the spinoff firm's initial financial statements are associated with an increase in equity sales for the spinoff firm's close private peers, suggesting a reduction in information uncertainty for those firms. Kim, Kim, Rosano and Suh (2025) finds that analyst forecast accuracy decreases and forecast dispersion increases for the spinoff firm's close peers after a spinoff. However, these effects are partially mitigated when the spinoff firm was not previously disclosed as a reportable segment by the pre-parent firm, suggesting that the spinoff firm's initial financial statements are informative. This thesis extends the spinoff literature in two ways. First, this thesis examines the spillover effects of spinoffs on the parent firm's peers, rather

[5] These streams of literature are discussed in detail in Chapter 3: Literature Review.

than the spinoff firm's peers. The setting enables the thesis to examine how characteristics of the pre-parent firm and differences between the pre-parent and post-parent firms affect the spillover effects of spinoffs. Specifically, this thesis examines the operational complexity of the pre-parent firm, the change in industry concentration between the pre-parent and post-parent firms, and the change in segment reporting between the pre-parent and post-parent firms. Second, this thesis identifies two additional mechanisms that helps explain the spillover effects of spinoffs on the parent firm's peers. Prior studies focus on the informational value of the spinoff firm's initial financial statements by examining whether the spinoff firm was previously disclosed as a reportable segment by the pre-parent firm (Kim and Suh 2023; Kim, Kim, Rosano, Suh 2025). In contrast, this thesis focuses on the role of cross-industry spinoffs in reducing analysts' information processing costs and the role of same-industry spinoffs as disruptive industry events.

This thesis also contributes to a growing literature that recognizes corporate restructurings as industry-wide events with spillover effects on peer firms. In addition to recent studies that examine the spillover effects of spinoffs, researchers have also examined how M&As and going-private transactions affect peer firms by reducing the amount of public information. Brown, Byard, Darrough and Suh (2024) find that analyst forecast accuracy decreases and forecast dispersion increases for the remaining peer firms after the acquisition of a public target firm. Similarly, Hinson and Piao (2025) show that going-private transactions are associated with lower analyst forecast accuracy for peer firms. Overall, these studies find that corporate restructurings that increase (decrease) public information can improve (deteriorate) the information environment of close peers. However, this thesis finds that corporate restructurings that increase public information, particularly same-industry spinoffs, may not always yield informational benefits for peer firms if the corporate restructurings are accompanied by heightened uncertainty due to changes in industry composition.

This thesis is organized into the following chapters. Chapter 2 provides background information about spinoffs. Chapter 3 reviews the relevant literature. Chapter 4 outlines the hypothesis development. Chapter 5 describes the sample selection and research design. Chapter 6 presents the descriptive, univariate and multivariate results. Chapters 7 and 8 discusses additional analyses and robustness tests, respectively. Chapter 9 concludes this thesis.

Chapter 2: Background Information

2.1 Introduction

This chapter provides background information on spinoffs and alternative forms of divestitures. Section 2.2 introduces spinoffs while Section 2.3 discusses cross-industry and same-industry spinoffs. Section 2.4 presents alternative forms of divestitures, such as asset sales, split-offs and carve-outs, and discusses the differences between spinoffs and these alternative divestitures.

2.2 Corporate Spinoffs

Spinoffs are a type of divestiture in which a parent firm separates a portion of its operations as one or more independent spinoff firms. Figure 1 provides an example. In the pre-spinoff period, the pre-parent firm has two divisions, Division A and Division B. The pre-parent firm announces its intention to separate Division B into an independent firm and retain Division A. The separation of the spinoff firm is initiated when the pre-parent firm distributes shares of the spinoff firm to the shareholders of the pre-parent firm as a dividend. Shareholders of the pre-parent firm receive shares of the spinoff firm on a pro-rata basis.[6] The pre-parent firm can distribute up to 100% of the spinoff firm's shares. If the pre-parent firm distributes at least 80% of these shares and relinquishes control of the spinoff firm, the spinoff can qualify for tax exemptions in the United States under Section 355 of the Internal Revenue Service (IRC) and the dividends received by the

[6] The ownership percentage in the spinoff firm is determined by the shareholder's ownership percentage in the pre-parent firm.

pre-parent firm's shareholders will be tax-free.[7] After the spinoff effective date, the post-parent firm retains Division A and the spinoff firm has control of Division B. If the post-parent firm retains ownership in the spinoff firm after the spinoff, it must have a valid business purpose and plans to divest the remaining shares within five years to maintain eligibility for tax-free treatment (Kidder 2011).

As a stand-alone firm, the spinoff firm must establish its own management team and board of directors. It can choose to recruit internally from the post-parent firm or hire external candidates.[8] If the spinoff firm is publicly listed, it will have its own shares traded on an exchange and it must adhere to listing requirements. The spinoff firm must also comply with regulatory requirements that are applicable to public firms, including the filing of its own audited financial statements.[9]

2.3 Cross-Industry and Same-Industry Spinoffs

Spinoffs can be categorized based on operational similarity between the parent and spinoff firms. Cross-industry spinoffs occur when a pre-parent firm separates its unrelated operations as a spinoff firm. Figure 2 provides an example. Suppose that Division A represents the core operations of the pre-parent firm. In a cross-industry spinoff, the spinoff firm takes control of Division B

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[7] Section 355 of the IRC includes other requirements that must be satisfied for a spinoff to quality for tax exemptions: (1) before the spinoff, the pre-parent firm controls the operations that constitute the spinoff firm by owning at least 80% of its shares (2) the spinoff is motivated by a legitimate corporate business purpose and is not a mechanism to distribute earnings (3) the pre-parent and spinoff firms are engaged in business for at least five years before the distribution date (4) the post-parent firm must have a valid business purpose to retain shares in the spinoff firm and these shares must be disposed within five years (Kidder 2011).

[8] Please refer to the following studies that examine the composition of the initial management team and board of directors of the spinoff firm (Seward and Walsh 1996; Wruck and Wruck 2002; Denis, Denis, and Walker 2015; Pham 2020).

[9] In some cases, spinoff firms can remain private. For example, in December 2016, Alphabet spun off its autonomous vehicle division, Waymo, which continues to operate as a private firm.

while the post-parent firm retains Division A. As a result, cross-industry spinoffs lead to post-parent and spinoff firms that are each less diversified and more focused on their core operations.

In contrast, same-industry spinoffs occur when the post-parent and spinoff firms operate in the same or related industries. Figure 3 provides an example. After the same-industry spinoff, the post-parent firm retains Division A and the spinoff firm controls Division B. Both the post-parent and spinoff firms operate in the same industry as the pre-parent firm.

2.4 Alternative Forms of Divestitures

Parent firms have multiple alternatives when they choose to divest their operations. Parent firms can sell and relinquish control of their divisions to a third-party buyer in exchange for consideration. For example, in May 2023, Meta sold Giphy, a platform used to search and use animated images, to Shutterstock for $53 million in cash. Unlike asset sales, spinoffs do not involve an exchange of consideration and ownership of the spinoff firm is transferred directly to the shareholders of the parent firm instead of a third-party buyer.

A split-off occurs when shareholders of the parent firm are given the option to exchange shares of the parent firm for shares in a newly created firm. For example, in July 2023, Johnson & Johnson announced a split-off of at least 80.1% of its consumer health business, Kenvue. Shareholders of Johnson & Johnson could exchange all, some, or none of their common stock of Johnson & Johnson for common stock of Kenvue. Unlike spinoffs, split-offs can create a more targeted shareholder base for the newly created firm as only interested shareholders will exercise their option to convert.

Another alternative is a carve-out, in which parent firms sell a minority stake in a newly created firm to external investors through an initial public offering (IPO). For example, in 2014, General Electric separated its consumer credit business, Synchrony Financial, by selling 15% of the new firm through an IPO and raising $2.88 billion USD while General Electric retained ownership of the remaining 85%. Unlike spinoffs, carve-outs attract new shareholders and raise equity capital.

Several studies have explored the determinants of selecting one form of divestiture over another. Important determinants include access to capital markets (Michaely and Shaw 1995), operating risks of the division to be separated (Khan and Mehta 1996), tax costs (Maydew, Schipper, and Vincent 1999), industry characteristics (Jain, Kini, and Shenoy 2011), information environment within the parent firm (Bergh, Johnson, and Dewitt 2008; Chemmanur and Liu 2011), and differences between the intrinsic value and market value of the parent firm (Prezas and Simonyan 2015).

Chapter 3: Literature Review

3.1 Introduction

This chapter provides a review of the relevant literature. Section 3.2 reviews the determinants of spinoffs. Section 3.3 discusses the direct effects of spinoffs on the parent and spinoff firms. Section 3.4 explores research on the spillover effects on peer firms. Section 3.5 examines the use of peer firm information by sell-side analysts. Finally, Section 3.6 reviews the spillover effects of corporate restructurings, including spinoffs, on peer firms.

3.2 The Determinants of Spinoffs

3.2.1 The Limitations of Firm Diversification

During the 1980s, many conglomerate firms focused on divesting their unrelated operations and increasing their corporate focus. This marked a significant change from the diversification strategies that were prevalent from the 1950s to the 1970s (Comment and Jarrell 1995). The percentage of single-segment listed firms increased from 38.1% to 55.7% while the average number of reported segments per firm declined from 2.53 to 1.94 (Comment and Jarrell 1995).

Jensen (1988) argues that diversification strategies can lead to inefficient and value-destroying investments, particularly when managers have excess borrowing capacity and substantial free cash flow. Empirical studies find evidence that diversification strategies can have adverse consequences on shareholder value. Morck, Shleifer, and Vishny (1990) find that acquisition announcement returns are lower if the target firm has unrelated operations. Lang and Stulz (1994) document a negative relationship between Tobin's Q and firm diversification, noting that diversified firms have lower Tobin's Q compared to portfolios constructed of single-segment firms. Berger and Ofek (1995) reveal that diversified firms are valued 13% to 15% less than the sum of the imputed market value of its segments. The diversification discount is also more pronounced for diversified firms with unrelated segments. Servaes (1996) finds that diversified firms have lower Tobin's Q than single-segment firms during the wave of mergers in the 1960s and 1970s. Overall, these studies suggest that diversification can hurt shareholder value maximization.

Consistent with Jensen (1988), empirical studies also provide evidence that diversified firms suffer from inefficient capital allocation, as strong performing segments can cross-subsidize poor performing segments and prevent capital from flowing to segments with greater investment opportunities. Berger and Ofek (1995) find that overinvestment and cross-subsidization of weak performing segments are positively associated with the diversification discount. Shin and Stulz (1998) document that segment-level investments are more sensitive to their own segment-level cash flows than the cash flows of other segments within the firm, challenging the notion that diversified firm can use their internal capital markets to allocate capital effectively. Rajan, Servaes, and Zingales (2000) reveal that firms with greater diversity in segment investment opportunities are associated with more cross-subsidization from segments with above-average opportunities to segments with below-average opportunities. Overall, these studies suggest that the diversification discount can arise from the misallocation of capital.

Understanding the limitations of diversification is relevant to understanding the determinants of spinoffs and divestitures more broadly. In a cross-industry spinoff, the pre-parent firm can separate its unrelated operations while retaining those essential to its core business. Empirical studies provide evidence that spinoffs and other divestitures can address concerns related to the diversification discount and capital misallocation. Dittmar and Shivdasani (2003) find asset sales and spinoffs that reduce the number of reported segments are associated with lower diversification discounts. Ahn and Denis (2004) document that pre-parent firms are valued at a diversification discount and the discount disappears after a spinoff. Studies that examine the impact of spinoffs on investment efficiency are discussed further in Section 3.3.3. Overall, these studies suggest that spinoffs and divestitures more broadly can address concerns associated with diversification strategies.

3.2.2 The Information Hypothesis

External financial statement users may face information uncertainty when they examine the operations and financial performance of a diversified firm. Diversified firms can be operationally complex due to their large size and presence across multiple industries. It may be difficult to reconcile these varying operations and form a coherent assessment of the firm's overall market value (Baik, Johnson, Kim and Yu 2023). These difficulties may be compounded by limited segment disclosures, which obscures the financial performance of individual divisions within the diversified firm (Nanda and Narayanan 1999). Segment disclosures for a particular division may be undisclosed, and when it is disclosed, it could be highly aggregated and uninformative.

The information hypothesis suggests that spinoffs can reduce information asymmetry between external users and the parent firm by increasing the transparency of divisional operations and financial performance. After a spinoff, the newly created spinoff firm is required to publicly file its own set of financial statements. These initial statements can provide incremental information about the separated division because previous information about the division was limited to segment disclosures by the pre-parent firm. In addition, the post-parent firm's financial statements reflect a narrower set of divisions. This simplification may enable external users to more easily relate firm-level financial performance to divisional-level financial performance.

Empirical studies provide mixed evidence on the information hypothesis. Krishnaswami and Subramaniam (1999) analyze 118 voluntary spinoffs between 1979 and 1993, finding that pre-parent firms have greater information asymmetry than their peers. They also document that firms with greater information asymmetry in the pre-spinoff period are more likely to initiate a spinoff. In contrast, Chen, Lin and Lin (2024) examine a larger sample of 414 spinoffs across a wider sample period from 1980 to 2014, and do not find consistent evidence. They argue that technological advancements such as EDGAR, and disclosure mandates, such as segment disclosure standards, have improved the information environment and reduced the informational incentives for spinoffs. Their study suggests that information asymmetry has become a less relevant determinant in recent years.

3.2.3 Other Determinants for Spinoffs

Other reasons have been cited as potential determinants of spinoffs. Cross-industry spinoffs allow the post-parent and spinoff firms to focus on their core activities, potentially improving their operational efficiency and strategic focus (Daley, Mehrotra, and Sivakumar 1997; Desai and Jain 1999). The spinoff firm can establish a management team and board of directors that comprise of industry experts to reinforce its strategic focus. The spinoff firm may also attract a targeted shareholder base as existing shareholders adjust their portfolios to align with their preferences while new investors with a specific interest in the spinoff firm purchase shares (Vijh 1994).[10] Increasing corporate focus can also motivate same-industry spinoffs if the parent and spinoff firms seek to specialize in distinct operations within the same major industry group. Prior literature defines same-industry spinoffs as spinoffs in which the parent and spinoff firms share the same two-digit SIC code (i.e., major industry group), which allows for strategic differentiation within a broadly defined industry classification (Daley, Mehrotra and Sivakumar 1997).[11]

Spinoffs can address concerns regarding incentive misalignment for divisional managers. In a diversified firm, divisional managers may have compensation contracts tied to both divisional and firm performance (Feldman 2016a). This structure can create agency costs if managers prioritize divisional profitability over investments that would benefit the firm. In addition, incentives tied to firm performance may fail to motivate divisional managers as they do not have decision-making control in other divisions. By separating the division as a spinoff firm, performance-based incentives for the manager of the spinoff firm are more aligned.

Spinoffs can also serve as a mechanism of divesting prior acquisitions that fail to provide anticipated synergies. Allen, Lummer, McConnell, and Reed (1995) examine a sample of spinoffs that involve previously acquired target firms and find that merger announcement returns are negatively associated with spinoff announcement returns.

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[10] This rationale is reflected by Larry Culp, CEO of General Electric, who explained the firm's decision to spin off its aviation and healthcare businesses in 2021. In an interview with CNBC, Larry Culp stated, "We know looking at spins elsewhere that the focus and accountability in a structure like this always increase…We will also stand up two new boards … chock-full of domain expertise that will help each of the businesses moving forward. I also think we will end up with investor bases geared toward each of these businesses."

[11] As an example, SPX Technologies spun off its flow technology segment as SPX Flow on September 25, 2015. Both firms operate in the same two-digit SIC code of 35. In the final version of the Form 10-12B filed on September 8, 2015, the key determinant of the spinoff was to increase corporate focus which can lead to a "distinct investment identity, enhanced strategic and management focus, alignment of incentive compensation and performance objectives, more efficient allocation of capital and strategic flexibility".

Finally, spinoffs can reflect the broader economic conditions and trends within an industry. Comment and Jarrell (1995) document a stark shift in managerial priorities as firms focused on diversification strategies in the 1950s to 1970s and specialization strategies in the 1980s and 1990s. More recently, there was a notable increase in spinoffs announcements during the COVID-19 pandemic. Practitioners suggest that the increase in spinoff announcements may be attributed to bearish market expectations and the rise of interest rates, as these changes have led to a decrease in IPOs and M&As, prompting firms to pursue spinoffs as an alternative strategy to generate shareholder returns (Dubner, Sharma, Singh, and Swanson 2023; Ward 2023).

3.3 The Direct Effects of Spinoffs

3.3.1 Shareholder Value

Early studies examine the impact of voluntary spinoff announcements on shareholder value within short-window periods for U.S. parent firms. Miles and Rosenfeld (1983) examine 55 spinoffs from 1963 to 1980 and find excess returns of 3.34% within a two-day window. Hite and Owers (1983) examine 123 spinoffs from 1963 to 1981 and report excess returns of 3.30% within a two-day window. Schipper and Smith (1983) examine 93 spinoff announcements from 1963 to 1981 and document excess returns of 2.84% within a two-day window. International studies also find consistent results. Veld and Veld-Merkoulova (2004) examine 156 spinoffs across 15 European countries and find excess returns of 2.62% within a three-day window. Chai, Lin and Veld (2018) examine 87 spinoffs from 1999 to 2013 that involved an Australian parent firm and report excess returns of 2.93% for a three-day window. Related studies also examine the wealth effects of spinoffs across longer time horizons and on different regulatory dates. Cusatis, Miles and Woolridge (1993) examine 146 spinoffs from 1965 to 1988 and find that post-parent (spinoff) firms have positive excess returns up to 36 months after the ex-dividend date (initial trade date) compared to peer firms.[12] Desai and Jain (1999) examine 155 spinoffs from 1975 to 1991 and report that spinoffs that increase corporate focus have higher abnormal returns than non-focus-increasing spinoffs up to three years after the announcement. Vijh (1994) examine 113 spinoffs from 1964 to 1990 and document excess returns of 3.03% on the spinoff ex-date. This study suggests that spinoffs attract new investors who are interested in holding shares in either the post-parent or spinoff firm, but not the pre-parent firm. Overall, these studies suggest that, on average, shareholders react positively to voluntary spinoff announcements.

Several studies also investigate the source of shareholder gains from spinoff announcements. Studies find higher announcement returns for spinoffs that involve a larger divestiture from the parent firm (Hite and Owers 1983; Miles and Rosenfeld 1983), increase in the parent firm's corporate focus (Hite and Owers 1983; Daley, Mehrotra and Sivakumar 1997), reduction in regulatory and tax constraints (Schipper and Smith 1983) and future merger activity (Hite and Owers 1983; Cusatis, Miles and Woolridge 1993). One stream of literature argues that shareholder gains come at the expense of bondholders as assets transferred from the parent firm to the spinoff firm cannot be claimed as collateral (Galai and Masulis 1976). Hite and Owers (1983) examine 53 senior securities for 31 parent firms from 1963 to 1981 and do not find abnormal returns around the announcement date. Within spinoffs that have positive announcement returns, Schipper and Smith (1983) examine the price reaction of 26 bonds for 13 spinoffs and bond ratings of 19 bonds for 16 spinoffs. They do not find consistent evidence that bond prices and bond ratings decline after a spinoff announcement. Parrino (1997) presents a case study of Marriott Corporation's 1993 spinoff of its management business. Within three days of the spinoff

[12] The ex-dividend date is the date in which the parent firm's stock trades without ownership rights to the spinoff firm.

announcement, the market-adjusted value of its common stock increased by 13.79% ($236.3 million) while the aggregate market-adjusted value of its 13 senior notes and debentures fell 16.51% ($333.3 million), suggesting a wealth transfer from bondholders to shareholders. Maxwell and Rao (2003) perform a large-sample study of 80 spinoffs from 1976 to 1997 and reveal that within the announcement month, bondholders experience negative abnormal returns of 88 basis points while shareholders experience a gain of 2.9%. Veld and Veld-Merkoulova (2008) examine 347 bonds from 91 spinoffs from 1995 to 2002 and document abnormal bond returns of 0.11% for a three-day window around the announcement. Overall, these studies suggest that the wealth transfer from bondholders to shareholders is not conclusive.

3.3.2 Operating Efficiency

Early studies used accounting metrics to measure the change in operating performance after a spinoff. Woo, Williard and Daellenbach (1992) examine the change in ROA for the spinoff firm within a five-year period around the effective date and find lower ROA in the post-spinoff period. Johnson, Klein, and Thibodeaux (1996) examine 104 spinoffs from 1975 to 1988 and reveal that the combined post-parent and spinoff firms have greater real asset growth and before-tax operating cash flows to sales than the pre-parent firm. Daley, Mehrotra and Sivakumar (1997) examine 85 spinoffs from 1975 to 1991 and document that cross-industry spinoffs lead to higher operating earnings for the combined post-parent and spinoff firms than the pre-parent firm. Desai and Jain (1999) examine 155 spinoffs from 1975 to 1991 and find consistent results that cross-industry spinoffs are associated with greater operating cash flow to total assets in the post-spinoff period than the pre-spinoff period. Chemmanur, Krishnan and Nandy (2014) differ from prior studies by measuring productivity using plant-level data from the U.S. Census Bureau. They examine 196 spinoffs of manufacturing firms from 1980 to 2000 and find that spinoffs improve total factor productivity through cost savings within plants that remain with the parent firm. In addition, they do not find evidence that plants allocated to the spinoff firm underperform in the pre-spinoff period, contradicting the notion that parent firms use spinoffs to separate their underperforming divisions. Overall, these studies suggest that spinoffs can improve operating performance from an accounting perspective, however, more research could examine how spinoffs affect real output.

3.3.3 Investment Efficiency

Gertner, Powers and Schardstein (2002) examine 160 spinoffs from 1981 to 1996 and find that capital expenditures of the spinoff firm become more positively associated with measures of investment opportunity in the post-spinoff period. The study also finds that cross-industry spinoffs and spinoffs with large announcement returns invest less in segments with low Tobin's Q and more in segments with high Tobin's Q. Dittmar and Shivdasani (2003) examine the investment patterns of the remaining segments of 278 parent firms that increased their corporate focus from asset sales and spinoffs. They find that underinvested (overinvested) segments in the pre-divestiture period, increased (decreased) their investments in the post-divestiture period. Ahn and Denis (2004) examine 106 spinoffs from 1981 to 1996 and reveal that pre-parent firms invest lower in high Tobin's Q segments and similarly in low Tobin's Q segments as single-segment peer firms in the pre-spinoff period. However, post-parent firms increase their investment in high Tobin's Q segments to match their single-segment peers. Overall, these studies suggest that spinoffs can enhance investment efficiency, consistent with the literature that recognizes inefficient capital allocation as a limitation of diversification.

3.3.4 Information Environment

The stock prices of diversified firms can be a noisy signal of divisional performance as it reflects the combined performance of all divisions within the firm. Analytical papers propose that spinoffs can improve the informational value of stock prices by splitting the pre-parent firm into multiple publicly traded firms, each with their own stock price. The separation allows the stock price of the spinoff firm to serve as a focused measure of its asset value, performance and managerial effectiveness (Aron 1991). Habib, Johnsen, and Naik (1997) suggest that having multiple stock prices can reduce information uncertainty about divisional asset values for uninformed investors and help managers better understand the value of their division, which can lead to better investment decisions. Analytical research also theorizes how spinoffs can affect the information production of institutional investors. Chemmanur and Liu (2011) theorize that the cost of information production decreases for post-parent and spinoff firms because they are smaller and less complex. They further suggest that institutional investors have industry expertise in certain segments of the pre-parent firm and will concentrate their information production on either the post-parent or spinoff firm, depending on which firm aligns with their expertise.

Several empirical studies examine how spinoffs impact the information environment of the parent firm, with most studies focusing on analyst forecast properties and analyst following. Krishnaswami and Subramaniam (1999) find that post-parent firms experience a decline in information asymmetry relative to peer firms in the post-spinoff period, suggesting that spinoffs enable external financial statement users to process information about divisional performance more accurately. They also find that pre-parent firms with higher information asymmetry are associated with higher announcement returns, suggesting that investors react more positively when information environments are weaker. Gilson, Healy, Noe, and Palepu (2001) examine 103 focus-increasing spinoffs, equity carve-outs and tracking stock offerings from 1990 to 1995 and document an increase in analyst following in the post-divestiture period, by industry specialists following the newly created firm, suggesting that divestitures that increase corporate focus can reduce the cost of analyst coverage. They also document that the increase in forecast accuracy after a divestiture is driven by industry specialists, suggesting that analysts can better leverage their industry expertise. Feldman, Gilson, and Villalonga (2014) examine 1,793 analyst reports for 62 spinoffs from 1985 to 2001 and reveal that reports discussing the conglomerate discount and the rationale for the spinoff are associated with higher forecast accuracy for the post-parent firm. Feldman (2016a) examines the analyst coverage decisions of 62 spinoffs from 1985 to 2001 and finds that coverage terminations and initiations are more common if the pre-parent firm separates its legacy business. They also find that analysts who terminate (initiate) coverage produce less (more) accurate forecasts in the pre-spinoff (post-spinoff) period than analysts who maintain coverage throughout. Campbell, Ettredge, Guo, Wiebe (2018) examine the similarity of 10-K disclosures between the pre-parent and spinoff firms for 130 spinoffs from 1996 to 2016. They document that pre-parent firms with greater information asymmetry, measured as stock illiquidity, bid-ask spreads and share turnover, are associated with spinoff firms with more incremental disclosures. They also document that their results are more pronounced for cross-industry spinoffs, suggesting that incremental disclosures are linked with operational motives. Overall, these studies suggest that spinoffs can improve the information environment. However, studies in non-US settings such as Europe (Veld and Veld-Merkoulova 2004) and Australia (Chai, Lin and Veld 2018) do not find a significant association between the pre-parent firm's information asymmetry and announcement returns. Moreover, Chen, Lin and Lin (2024) do not find consistent results when using a broader and more recent sample period.

3.4 Degree of Spillover Effects Between Peer Firms

Firms that operate in the same or related industries share common characteristics, such as exposure to macroeconomic conditions, business models, product offerings and customer bases. These commonalities can lead to positively correlated fundamentals between peer firms, creating information complementarity (Banerjee, Dasgupta, Shi and Yan 2023). Financial statement users may perceive these complementarities and use information from one firm to assess the market value of a peer firm. Empirical research finds evidence of information spillovers between peer firms following earnings announcements (Foster 1981), management forecasts (Baginski 1987) and accounting fraud disclosures (Gleason, Jenkins, and Johnson 2008). Related studies further differentiate these spillover effects by using industry classification codes to distinguish between "close" and "distant" peers. Banerjee, Dasgupta, Shi and Yan (2023) document that fraud disclosures lead to higher implied cost of capital for close peers, relative to distant peers. Close peers share the same 4-digit SIC code or 3-digit SIC code as the fraud firm, while distant peers share the same 2-digit SIC code but different 3-digit SIC code. Beatty, Liao, and Yu (2013) reveal that fraud-induced overstated earnings are associated with higher capital expenditures for close peers, relative to distant peers. Close peers share the same three-digit SIC code as the fraud firm, while distant peers share the same two-digit SIC code, but different three-digit SIC code. Overall, these findings suggest that information spillovers are more pronounced within close peers than distant peers.

3.5 Use of Peer Firm Information by Sell-Side Analysts

Sell-side analysts are sophisticated financial statement users who process information from multiple peer firms to forecast earnings, predict stock prices and provide stock recommendations.

Ramnath (2002) finds that earning announcements of early reporting firms are informative to analysts when they revise their forecasts for subsequent reporting industry peers. De Franco, Hope and Larocque (2015) discuss the importance of selecting appropriate peer firms for firm valuation using a price-earnings multiple approach. Firm earnings are capitalized using a price-earnings multiple that is derived from a group of comparable peer firms, highlighting the importance of understanding peer firm information. Survey evidence from Brown, Call, Clement, and Sharp (2015) document that sell-side analysts consider industry knowledge to be the most important input in their earnings forecasts and stock recommendations.

Prior studies also document that analysts have industry expertise. Boni and Womack (2006) document that 76% of analysts follow firms within one GICS industry. De Franco, Hope and Larocque (2015) examine analyst reports and reveal that 92% of peer firms are within the same two-digit GIC industry. Sell-side analysts also believe that industry knowledge is the most important determinant of their compensation, suggesting a strong financial incentive to develop industry expertise (Brown, Call, Clement and Sharp 2015)

Related studies also suggest that analyst coverage decisions reflect information complementarities between the firms they follow. Muslu, Rebello, and Xu (2014) find that returns of recommended stocks covary with other stocks in the analyst's portfolio, suggesting that analysts produce information relevant to multiple covered firms. Ali and Hirshleifer (2020) demonstrates that peer firms with shared analyst coverage exhibit correlated sales and profit growth. Kaustia and Rantala (2021) document that peer firms connected by shared analyst coverage exhibit greater similarities than those connected by common industry classifications. Banerjee, Dasgupta, Shi and Yan (2023) reveal that spillover effects of fraud disclosures on the implied cost of capital of peer firms are more pronounced if the fraud firm and peer firm share analyst coverage. Overall, these studies recognize the importance of peer firm information in analysts' output. They also demonstrate the ability of analyst to perceive information complementarities and incorporate information from peer firms.

3.6 Spillover Effects of Corporate Restructurings

A recent stream of literature examines the spillover effects of corporate restructurings. While corporate restructurings have direct effects on the firms that initiate them, they can have industry-wide consequences on peer firms, particularly if these restructurings affect the quantity and quality of public information available to financial statement users. For example, acquisition of public target firms and going-private transactions can reduce the quantity and quality of public information as private U.S. firms rarely disclose their financial reports voluntarily (Minnis and Shroff 2017). These implications can negatively affect the information set of financial statement users, particularly analysts, who rely on information from peer firms to produce high-quality outputs. Brown, Byard, Darrough and Suh (2024) examine 815 M&A transactions in which a public target firm is delisted and does not provide public financial statements afterwards. Their study finds that forecast accuracy declines and forecast dispersion increases for peer firms up to six quarters after the acquisition. Hinson and Piao (2025) examine the impact of 482 going-private transactions from 2006 to 2017 on the disclosure quality of peer firms. After the transaction, they find that analyst forecast accuracy declines for peer firms. Their results are more pronounced if the going-private firm provided high-quality disclosures within the industry beforehand.

Unlike M&A and going-private transactions, spinoffs can lead to an increase in the quantity and quality of public information. Kim and Suh (2023) examine if the creation of a spinoff firm from 89 spinoffs between 2010 and 2019 can reduce information uncertainty within the spinoff firm's industry and enable private firms to raise more equity capital. Their study reveals that private peer firms sell more equity in the post-spinoff period than the pre-spinoff period. Their results are more pronounced if the operations of the spinoff firm were not disclosed through segment disclosures by the pre-parent firm, suggesting that the spinoff firm's initial financial statements are informative. In a recent paper, Kim, Kim, Rosano, and Suh (2025) examine the impact of 82 spinoffs from 2010 to 2019 on the analyst forecast accuracy and dispersion of the spinoff firm's peers. They find that, on average, peer firms have lower forecast accuracy and higher forecast dispersion in the post-spinoff period. However, if the spinoff firm was not previously disclosed as a segment by the pre-parent firm, peer firms exhibit higher forecast accuracy and lower forecast dispersion, relative to spinoffs in which the spinoff firm was previously disclosed. While their study shares some similarities with this thesis, there are important distinctions. First, this thesis examines the spillover effects of spinoffs on the parent firm's peers rather than the spinoff firm's peers. Second, this thesis distinguishes between cross-industry and same-industry spinoffs to identify additional mechanisms, other than segment reporting, to explain the spillover effects of spinoffs. Third, this thesis provides more causal evidence by comparing the spillover effects of spinoffs between close and distant peers. Fourth, the forecast accuracy analysis is conducted at the analyst level, instead of the firm level, which allows the regression analysis to control for forecast, analyst and brokerage characteristics, and changes in analyst coverage around the spinoff.

Chapter 4: Hypothesis Development

4.1 Introduction

In this section, I present two sets of hypotheses. The first set of hypotheses focuses on the impact of cross-industry spinoffs on the analyst forecast properties of the parent firm's close peers. The second set of hypotheses focuses on the impact of same-industry spinoffs on the forecast properties of the parent firm's close peers. By developing separate hypotheses for cross-industry and same-industry spinoffs, this thesis recognizes how the operating similarity between the parent and spinoff firms affect the mechanisms that explain the spillover effects.

4.2 Cross-Industry Spinoffs and Analysts' Information Acquisition Costs

In a cross-industry spinoff, the pre-parent firm divests its unrelated operations into a newly created spinoff firm. Cross-industry spinoffs may reduce analysts' information processing costs and facilitate information spillovers between close peers for several reasons. First, the divestiture of the pre-parent firm's unrelated operations suggest that the post-parent firm is less diversified and less complex. Prior studies find that analysts specialize within industries (Boni and Womack 2006; Brown, Call, Clement and Sharp 2015; De Franco, Kothari, Verdi 2015; Bradley, Gokkaya, Liu, and Xie 2017) and incorporate information from multiple industry peers (Ramnath 2002; Bradshaw, Miller, and Serafeim 2009; De Franco, Kothari, and Verdi 2011; Brown, Byard, Darrough and Suh 2024; Hinson and Piao 2025). Analysts who follow a diversified pre-parent firm may incur higher processing costs and thereby rely less heavily on the information produced by the pre-parent firm as their expertise is limited to certain segments. Frankel, Kothari, and Weber (2006) document smaller stock price reactions to analyst reports for multi-segment firms, suggesting that analysts' reports are less informative when their expertise is limited. Cohen and Lou (2012) reveal that analysts incorporate industry-level information slower into forecasts for diversified firms than for pseudo-diversified firms comprised of single-segment firms. If cross-industry spinoffs lead to less diversified post-parent firms and lower analysts' information processing costs, it may be easier for analysts to incorporate information from the post-parent firm into the earnings forecasts of its close peers, thereby leading to higher forecast accuracy and lower forecast dispersion.

Second, diversified firms may have opaque information environments that heighten information uncertainty for external financial statement users, making it more difficult to assess the internal operations and financial performance of the firm. Bushman, Chen, Engel, and Smith (2004) suggest that diversified firms adopt certain governance mechanisms to mitigate moral hazard concerns that arise from their opaque information environments. Baik, Johnson, Kim, and Yu (2023) find that firms with greater organizational complexity, measured as a principal component of the number of subsidiaries, hierarchical layers, and industries in which the firm operates, are associated with lower analyst forecast accuracy and higher forecast dispersion. If cross-industry spinoffs lead to less diversified post-parent firms, these firms may have less opaque information environments and analysts may face less information uncertainty, thereby facilitating information spillovers between the post-parent firm and its close peers.

Overall, I hypothesize that after a cross-industry spinoff, forecast accuracy will increase and forecast dispersion will decrease for the parent firm's close peers. In addition, I hypothesize that the increase in forecast accuracy and decrease in forecast dispersion will be more pronounced if analysts' information processing costs are reduced to a greater extend after a cross-industry spinoff. To proxy for the reduction in analysts' information processing cost, I count the number of business segments of the pre-parent firm to measure the firm's operational complexity, hypothesizing that the reduction in information processing costs is greater for pre-parent firms that are more complex. This leads to the following hypotheses:

H1A: After a cross-industry spinoff, forecast accuracy will increase for the parent firm's close peers, relative to its distant peers.

H1B: After a cross-industry spinoff, forecast dispersion will decrease for the parent firm's close peers, relative to its distant peers.

H2A: After a cross-industry spinoff, the increase in forecast accuracy is more pronounced for pre-parent firms that are operationally complex.

H2B: After a cross-industry spinoff, the decrease in forecast dispersion is more pronounced for pre-parent firms that are operationally complex.

4.3 Same-Industry Spinoffs

In a same-industry spinoff, the post-parent and spinoff firms operate in the same or related industries. Ex-ante, it is unclear how same-industry spinoffs will affect the analyst forecast properties of the parent firm's close peers. Same-industry spinoffs can be disruptive industry events as the contraction of the parent firm and the introduction of the spinoff firm as a stand-alone competitor can affect the peer firm's industry composition, potentially complicating the forecasting process for analysts. However, same-industry spinoffs can also increase the quantity and quality of public information from the spinoff firm's initial financial statements and from incremental segment reporting from the post-parent or spinoff firm. Sections 4.3.1 and 4.3.2 will elaborate on these opposing mechanisms. Given the opposing nature of these mechanisms, I predict a null hypothesis on the impact of same-industry spinoffs on the forecast accuracy and forecast dispersion of the parent firm's close peers.

H3A: After a same-industry spinoff, forecast accuracy will not change for the parent firm's close peers, relative to its distant peers.

H3B: After a same-industry spinoff, forecast dispersion will not change for the parent firm's close peers, relative to its distant peers.

4.3.1 Changes in Industry Composition

In a same-industry spinoff, the post-parent and spinoff firms operate in the same or related industries. Same-industry spinoffs can affect the close peers' industry composition as the contraction of the parent firm and the introduction of the spinoff firm can decrease industry concentration and increase competition.

Changes in industry composition can be associated with heightened uncertainty for several reasons. Managerial operating decisions can reflect changes in industry composition, which affects the riskiness of future cash flows and earnings (Hou and Robinson 2006). Firms that operate in less concentrated industries can have less pricing power and less flexibility to absorb cost shocks, leading to greater uncertainty about future profitability (Gaspar and Massa 2006). Irvine and Pontiff (2009) finds that idiosyncratic risk increases after industry deregulation, which lowers the barriers to entry and intensifies competition. Cross-sectional analyses also find that firms in less concentrated industries have higher volatility of idiosyncratic returns (Gaspar and Massa 2006; Hou and Robinson 2006; Irvine and Pontiff 2009).

Related studies also use a series of cross-sectional regressions to find that firms in less concentrated industries are associated with lower forecast accuracy and higher forecast dispersion (Gaspar and Massa 2006; Datta, Iskandar-Datta 2011). Haw, Hu and Lee (2015) use a panel dataset of international firms from 1990 to 2008 and find consistent results.

Overall, if same-industry spinoffs are disruptive industry events that affect industry composition, I hypothesize that forecast accuracy will decrease and forecast dispersion will increase after a same-industry spinoff. In addition, I hypothesize that the decrease in forecast accuracy and the increase in forecast dispersion will be more pronounced for peers that operate in industries that become less concentrated in the post-spinoff period.[13] This leads to the following set of hypotheses:

H4A: After a same-industry spinoff, the decrease in forecast accuracy will be more pronounced for close peers, relative to distant peers, that operate in industries that become less concentrated in the post-spinoff period.

H4B: After a same-industry spinoff, the increase in forecast dispersion will be more pronounced for close peers, relative to distant peers, that operate in industries that become less concentrated in the post-spinoff period.

However, it may be equally challenging to forecast earnings of firms in concentrated industries if firms provide fewer disclosures (Harris 1998; Botosan and Stanford 2005). Ali, Klasa, and Yeung (2014) find that firms in concentrated industries issue fewer management forecasts

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[13] As mentioned in Section 3.2.3, parent and spinoff firms can increase their corporate focus within same-industry spinoffs if each firm specializes in distinct operations within the same major industry group. The consequences of industry disruption may outweigh the potential benefits of increasing corporate focus as the benefits of separating unrelated operational activities is less pronounced if those activities are more related.

with shorter time horizons. They also find that these firms are associated with lower forecast accuracy and higher forecast dispersion.

4.3.2 Incremental Segment Disclosures

Post-parent firms, relative to pre-parent firms, can provide incremental segment disclosures for several reasons. Since the post-parent firm is smaller than the pre-parent firm, operating segments in the pre-spinoff period may become reportable operating segments in the post-spinoff period if they exceed the quantitative reporting thresholds under ASC 280.[14] The post-parent firm may also redefine its segments to reflect changes in how the chief operating decision maker evaluates the post-parent firm's operations, which may differ from how the operations of the pre-parent firm were assessed. For example, on September 25, 2015, SPX Technologies spun off its flow technology segment as SPX Flow while retaining its thermal equipment and services segment. In SPX Technologies' initial financial statement after the spinoff, the firm restructured its segment disclosures by breaking up its thermal equipment and services segment into three segments: HVAC, detection and measurement and power.

Spinoff firms can also provide additional segment disclosures than those previously offered by the pre-parent firm regarding the spinoff firm's operations. For example, on June 29, 2018, Autoliv Inc. spun off its electronics segment as Veoneer Inc. In Veoneer Inc.'s initial financial report after the spinoff, it disclosed two segments: electronics and brake systems.

[14] Under ASC 280-10-50-12, operating segments report separate financial information if the operating segments' financial performance exceeds any of the following criteria: (1) If the reported revenue is at least 10% of the combined revenue for all operating segments in the firm (2) the absolute profit (loss) is at least 10% of the combined absolute profit (loss) of the operating segments that reported a profit (loss) (3) assets are at least 10% of the combined assets of all operating segments.

Prior studies use the adoption of SFAS 131 to examine the informativeness of incremental segment disclosures.[15] Berger and Hann (2003) find that analyst forecast accuracy improves for firms that reported more segments after the adoption of SFAS 131. Ettredge, Kwon, Smith and Zarowin (2005) demonstrate that the adoption of SFAS 131 increase the future earnings response coefficient for multi-segment firms and single-segment firms that transitioned to multi-segment firms in the post-adoption period. Cho (2015) document that investment efficiency improves for firms that revise their segment disclosures following the adoption of SFAS 131, suggesting that SFAS 131 improved the monitoring ability of external stakeholders. These studies suggest that incremental segment disclosures are informative to different financial statements users.

Overall, if incremental segment disclosures are informative to analysts, I hypothesize that the decrease in forecast accuracy and the increase in forecast dispersion will be less pronounced for spinoffs that provide incremental segment disclosures. This leads to the following set of hypotheses:

H5A: After a same-industry spinoff, the decrease in forecast accuracy is less pronounced for spinoffs that provide incremental segment disclosures.

H5B: After a same-industry spinoff, the increase in forecast dispersion is less pronounced for spinoffs that provide incremental segment disclosures.

[15] The adoption of SFAS 131 increased the number of reported segments and provided more disaggregated information (Herrmann and Thomas 2000; Street, Nichols, and Gray 2000; Berger and Hann 2003).

Chapter 5: Sample Selection and Research Design

5.1 Sample Selection

5.1.1 Spinoff Transactions

I obtain spinoff information from Form 10-12B filings in SEC EDGAR. Form 10-12B is a mandatory filing for firms that issue new stock through spinoffs. The filing includes an information statement that details the pro-rata distribution of the spinoff firm's shares, the rationale for the spinoff, and the expected effective date. The sample period extends from January 1, 2010, to December 31, 2018, to mitigate confounding effects from the 2008 financial crisis and the 2020 COVID-19 pandemic. The initial sample consists of 244 spinoffs.

I validate each filing to ensure it is related to a spinoff by excluding share registrations unrelated to spinoffs and misclassified filings (e.g., Form 10-SB and Form 12B-25). I exclude spinoffs that involve concurrent corporate restructurings such as M&As and bankruptcies. To ensure that spinoffs have financial statement consequences, I validate that the pre-parent and post-parent firms provide financial reports before and after the spinoff, respectively, while the spinoff firm provides financial reports after the spinoff. Finally, I exclude spinoffs if the parent or spinoff firms are foreign issuers, financial firms, and do not match with Compustat or CRSP. These steps result in 110 spinoffs. Finally, the parent firm of each spinoff must have at least one close peer and one distant peer. Consistent with prior spillover studies, I define close and distant peers based on their industry classification codes (Beatty, Liao and Yu 2013; Banerjee, Dasgupta, Shi and Yan 2023). Close peers share the same four-digit SIC code as the pre-parent firm in the year before the initial filing date of the Form 10-12B, while distant peers share the same two-digit SIC code, but different three-digit SIC code. The final sample consists of 76 spinoffs. Table 1 Panel A provides additional details.

5.1.2 Forecast Accuracy Analysis

For each spinoff, I identify the analysts who provide quarterly EPS forecasts for the close and distant peers in the pre-spinoff and post-spinoff periods.[16] I obtain the most recent quarterly EPS forecast for the next fiscal quarter within 90 days before the earnings announcement date, and the actual quarterly EPS, from the IBES Detail History File. The pre-spinoff period is defined as six quarters preceding the initial filing date of the Form 10-12B. The post-spinoff period is defined as six quarters following the initial filing date of a financial report by the post-parent firm after the spinoff effective date.

To ensure a balanced sample, I require each peer firm to file at least three financial reports (i.e., 10-Q or 10-K) in both the pre-spinoff and post-spinoff periods. Analysts must also provide at least three quarterly forecasts in both the pre-spinoff and post-spinoff periods for each peer firm they cover. This requirement mitigates a concern that changes in forecast properties are driven by changes in analyst coverage. The sample for the forecast accuracy analysis is constructed at the spinoff-peer firm-analyst-quarter level, resulting in 1,107 close peers, 3,928 distant peers, and 183,383 observations. Table 1 Panel B provides additional details on the sample selection while Table 5 provides details on the number of close and distant peers for each spinoff.

5.1.3 Forecast Dispersion Analysis

Quarterly forecast dispersion is calculated for peer firms with at least three quarterly forecasts in a quarter. To ensure a balanced sample, peer firms must have at least three forecast dispersion observations in both the pre-spinoff and post-spinoff periods. The sample is constructed

[16] Anonymous analysts that have ANALYS code of 00000 are removed as this code can comprise of multiple individual analysts. This will make it difficult to control for analyst characteristics.

at the spinoff-peer firm-quarter level, resulting in 290 close peers, 1,863 distant peers, and 23,778 observations. Table 1 Panel C provides additional details on the sample selection. Table 6 provides details on the number of close and distant peers for each spinoff.

5.2 Research Design

5.2.1 Forecast Accuracy Analysis

$$\begin{aligned} FError_{s,i,j,t} = {} & \alpha + \beta_1 Post_t + \beta_2 Peer_{s,j} + \beta_3 Post{\times}Peer_{s,j,t} + \beta_4 Horizon_{i,j,t} + \beta_5 Gen\_Exp_{i,j,t} \\ & + \beta_6 Firm\_Exp_{i,j,t} + \beta_7 Port\_Size_{i,t} + \beta_8 SIC2\_Count_{i,t} + \beta_9 Broker\_Size_{i,t} \\ & + \beta_{10} Size_{j,t-1} + \beta_{11} MTB_{j,t-1} + \beta_{12} ROA_{j,t-1} + \beta_{13} Leverage_{j,t-1} + \beta_{14} Loss_{j,t-1} \\ & + \beta_{15} Ret\_Vol_{j,t} + \beta_{16} Analyst\_Follow_{j,t} + \beta_{17} HHI_{j,t} + \beta_{18} Delist_{j,t} \\ & + \beta_{19} IPO_{j,t} + EventFE_s + Analyst{\times}EventFE_{s,i} + Firm{\times}EventFE_{s,j} \\ & + QtrFE_t + \varepsilon_{s,i,j,t} \end{aligned} \quad (1)$$

Equation 1 examines the impact of cross-industry and same-industry spinoffs on the forecast accuracy of the parent firm's close peers, relative to distant peers. *FError* represents the absolute forecast error, measured as the absolute difference between the peer firm's quarterly EPS forecast and the actual quarterly EPS, scaled by the peer firm's share price at the beginning of the quarter, times 100. *FError* is measured for analyst *i*, following peer firm *j*, in quarter *t,* for spinoff *s*. Higher values of *FError* represent lower forecast accuracy while lower values of *FError* represent higher forecast accuracy. *Post* equals 1 for the six-quarter period following the initial filing date of a financial report by the post-parent firm after the spinoff effective date. *Post* equals 0 for the six-quarter period preceding the initial filing date of the Form 10-12B. *Peer* equals 1 for close peers that share the same 4-digit SIC code as the parent firm in the year before the initial filing date of the Form 10-12B. *Peer* equals 0 for distant peers that share the same two-digit SIC code but different three-digit SIC code. The variable of interest is *Post×Peer*, whose coefficient

β_3 represents the change in forecast accuracy for close peers, relative to distant peers, across the pre-spinoff and post-spinoff periods.

Equation 1 includes several control variables. First, I control for forecast, analyst and brokerage characteristics. *Horizon* measures the number of days between the forecast date and the earnings announcement date. *Gen_Exp* measures an analyst's general forecasting experience and equals the number of prior calendar quarters an analyst appears in IBES. *Firm_Exp* measures an analyst's firm expertise and equals the number of previous quarterly forecasts made by an analyst for a particular firm. I predict that *Gen_Exp* and *Firm_Exp* are positively associated with forecast accuracy. *Port_Size* equals the number of unique firms an analyst covers for a quarter. *SIC2_Count* equals the number of unique 2-digit SIC codes in an analyst's portfolio for a quarter. *Port_Size* and *SIC2_Count* measures the complexity of an analyst's portfolio and I predict that both measures are negatively associated with forecast accuracy (Clement 1999). *Broker_Size* measures the amounts of resources that brokerages provide their analysts and equals the number of analysts employed by a brokerage in a calendar quarter. I predict that *Broker_Size* is negatively associated with forecast accuracy.

Second, I control for peer firm characteristics. *Size* is the natural log of total assets in the prior quarter. *MTB* is the market-to-book ratio in the prior quarter. *ROA* is the income before extraordinary items scaled by total assets in the prior quarter. *Leverage* is total liabilities scaled by total assets in the prior quarter. *Loss* equals 1 if income before extraordinary items is negative in the prior quarter. *Ret_Vol* is the standard deviation of daily stock returns in the past year. *Analyst_Follow* is the number of analysts that covered the firm in the prior quarter. I predict that less profitable firms, loss firms, and firms with higher return volatility are associated with lower forecast accuracy, while firms with greater analyst following are associated with higher forecast accuracy.

Third, I control for industry characteristics. *HHI*, the Herfindahl-Hirschman Index, is measured as the sum of squared market share of a firm's annual net sales in a four-digit SIC code. *Delist* reflects the decrease in public information due to going-private transactions and acquisitions of public target firms (Brown, Byard, Darrough and Suh 2024; Hinson and Piao 2025). *Delist* equals 1 if a forecast is made within 6 quarters after the filing date of the last financial report of a delisting firm within the same four-digit SIC. *IPO* reflects the increase in public information from IPOs. *IPO* equals 1 for the quarter of the initial financial statements of the IPO firm within a four-digit SIC code.

Finally, I include a robust set of fixed effects and clustered standard errors. Event fixed effects controls for time-invariant factors within each spinoff. Analyst × event and firm × event fixed effects control for time-invariant factors within each analyst-spinoff and peer firm-spinoff combination, respectively. Quarter-cohort fixed effects control for time trends and are structured based on the relative period of the quarter to the spinoff effective date. Standard errors are clustered for peer firms which corresponds to the treatment effect.

5.2.2 Forecast Dispersion Analysis

$$\begin{aligned} Disp_{s,j,t} = {} & \alpha + \beta_1 Post_t + \beta_2 Peer_{s,j} + \beta_3 Post \times Peer_{s,j,t} + \beta_4 Size_{j,t-1} + \beta_5 MTB_{j,t-1} \\ & + \beta_6 ROA_{j,t-1} + \beta_7 Leverage_{j,t-1} + \beta_8 Loss_{j,t-1} + \beta_9 Ret\_Vol_{j,t} \\ & + \beta_{10} Analyst\_Follow_{j,t} + \beta_{11} HHI_{j,t} + \beta_{12} Delist_{j,t} + \beta_{13} IPO_{j,t} + EventFE_s \\ & + Firm \times EventFE_{s,j} + QtrFE_t + \varepsilon_{s,j,t} \end{aligned} \tag{2}$$

Equation 2 examines the impact of cross-industry spinoffs and same-industry spinoffs on the forecast dispersion of the parent firm's close peers, relative to distant peers. *Disp* represents forecast dispersion, measured as the standard deviation of quarterly forecasts, scaled by the peer firm's stock price at the beginning of the quarter, times 100. *Disp* is measured for peer firm *j*, in quarter *t,* for spinoff *s*. Forecast dispersion represents the level of information uncertainty between analysts following the same peer firm. Higher values of *Disp* indicate higher information uncertainty while lower values of *Disp* indicate lower information uncertainty. Unlike Equation 1, Equation 2 is compiled at the spinoff–peer firm–quarter level and does not include control variables for forecast characteristics, analyst characteristics and brokerage characteristics and analyst × event fixed effects.

Chapter 6: Descriptive, Univariate and Multivariate Results

6.1 Descriptive Results

Table 2 presents the number of spinoffs per year. The variation in spinoff frequency across the sample period suggests that spinoff activity follows a cyclical pattern. The sample includes 35 cross-industry spinoffs and 41 same-industry spinoffs. Table 3 presents the industry of the pre-parent firm, categorized by its two-digit SIC code. Across the 76 spinoffs, the pre-parent firm operates in 20 different industries. The top three industries with the highest number of spinoffs are all within the manufacturing sector.

Table 4 presents the assets, revenue and market value of the parent firm and the spinoff firm. Panel A presents the pre-parent firm at the fiscal year-end before the filing date of the Form 10-12B while Panel B presents the post-parent firm at the immediate fiscal year-end after the spinoff effective date. The assets, revenue and market value of the post-parent firm are lower than those of the pre-parent firm, indicating that the separated operations are no longer consolidated with the post-parent firm. Panel C presents the spinoff firm at the immediate fiscal year-end after the spinoff effective date. As expected, the assets, revenue and market value of the spinoff firm are approximately the difference between those of the pre-parent and post-parent firms. The combined market value of the of the post-parent and spinoff firms exceeds the market value of the pre-parent firm, suggesting that spinoffs, on average, unlocks shareholder value.

Tables 5 and 6 present the number of close and distant peers for each spinoff in the forecast accuracy analysis and the forecast dispersion analysis, respectively. As expected, the number of distant peers exceed the number of close peers as close peers have more stringent industry classification requirements.

Table 7, Panel A presents the descriptive statistics for the dependent and control variables for the forecast accuracy analysis while Panel B presents similar information for the forecast dispersion analysis. Both tables are presenting the descriptive statistics for the pooled sample of spinoffs. In the forecast accuracy analysis, the average forecast is made 49.55 days before the earnings announcement date. The average analyst has 15.84 quarters of firm-specific forecasting experience and 39.41 quarters of general forecasting experience. The average analyst also follows 13.87 firms and 3.24 unique two-digit SIC industries in their portfolio. Finally, the mean (median) *FError* is 0.36 (0.13), and the mean (median) *Disp* is 0.18 (0.07).

6.2 Univariate Results

Table 8, Panel A presents the univariate results for the forecast accuracy analysis using the pooled sample of spinoffs. *FError* and *Post* are positively correlated, which suggests that forecast accuracy decreases in the post-spinoff period. *FError* and *Peer* are positively correlated, which suggests that close peers, relative to distant peers, have lower forecast accuracy. The univariate results between *FError* and the control variables are relatively consistent with expectations. Analysts with more general and firm-specific forecasting experience and employment at larger brokerages have higher forecast accuracy, while analysts who cover more firms have lower forecast accuracy. Firms with greater size, ROA and analyst following have higher forecast accuracy while firms with losses, higher return volatility and higher leverage have lower forecast accuracy. Industries with greater concentration also have higher forecast accuracy. Panel B presents the univariate results for the forecast dispersion analysis using the pooled sample of spinoffs. *Disp* is positively and significantly correlated with *Post*, which suggests that forecast dispersion increases in the post-spinoff period. The correlations between *Disp* and the control variables are consistent with Panel A.

6.3 Multivariate Results

6.3.1 Main Results for Cross-Industry Spinoffs

Table 9 presents the multivariate results on the impact of cross-industry spinoffs on the forecast accuracy of the parent firm's close peers, relative to its distant peers, using different regression specifications for fixed effects and clustering. Across all regression specifications, I find that *Post×Peer* is negative and insignificant, suggesting that, on average, the separation of the parent firm's unrelated operations does not affect analyst forecast accuracy for close peers, relative to distant peers. I do not find support for H1A.

Table 10 presents the multivariate results on the impact of cross-industry spinoffs on the forecast dispersion of the parent firm's close peers, relative to distant peers. Across all regression specifications, I find that *Post×Peer* is negative and significant at either the 5% or 1% level, suggesting that cross-industry spinoffs can lower analysts' information processing costs for the parent firm's close peers, relative to its distant peers. I find support for H1B.

6.3.2 Main Results for Same-Industry Spinoffs

Table 11 presents the results on the impact of same-industry spinoffs on the forecast accuracy of the parent firm's close peers, relative to its distant peers. Across all regression specifications, I find that *Post×Peer* is positive and significant at the 1% level, suggesting that same-industry spinoffs lower forecast accuracy for the parent firm's close peers, relative to its distant peers. As a result, I do not find support for H3A.

Table 12 presents the results on the impact of same-industry spinoffs on the forecast dispersion of the parent firm's close peers, relative to distant peers. Across all regression specifications, I find that *Post×Peer* is positive and significant at the 1% level, suggesting that same-industry spinoffs increase information uncertainty for the parent firm's close peers, relative to its distant peers. As a result, I do not find support for H3B.

Overall, the results in Sections 6.3.1 and 6.3.2 suggest that the spillover effects of spinoffs on the analyst forecast properties of the parent firm's close peers, relative to distant peers, is contingent on the operational similarity between the parent and spinoff firms.[17] The following sections examine the potential mechanisms that drive these results.

6.3.3 Cross-Industry Spinoffs – Information Acquisition Costs

In this section, I examine whether the impact of cross-industry spinoffs on the forecast accuracy and forecast dispersion of the parent firm's close peers, relative to its distant peers, are driven by a reduction in the analysts' information acquisition costs. I presume that after a cross-industry spinoff, the reduction in the analysts' information acquisition costs is greater for pre-parent firms that are operationally complex. To assess the complexity of the pre-parent firm, I hand-collect segment disclosure data for the pre-parent firm in the fiscal period preceding the initial filing of the Form 10-12B and count the number of business segments that are disclosed.[18]

[17] In untabulated tests, I do not find results when examining the impact of cross-industry and same-industry spinoffs on the forecast optimism of analysts following the parent firm's close peers, relative to its distant peers.

[18] Pre-parent firms that only report geographic segments are treated as a single-segment firms as the theoretical construct focuses on the challenges analysts face when their industry expertise does not extend across all segments of a diversified firm. In addition, segments labelled as "corporate", "intercompany eliminations" and "others" are excluded.

Table 13, Panel A presents the descriptives statistics on the number of segments in the pre-parent firm. Of the 35 cross-industry spinoffs, the number of segments range from two to seven while three is the most frequent number of segments. Table 13, Panel B presents the multivariate results when the sample of cross-industry spinoffs is split at the median number of business segments in the pre-parent firm. Columns 1 and 2 present the forecast accuracy analysis. In Column 1, *Post×Peer* is positive and insignificant while in Column 2, *Post×Peer* is negative and insignificant. These results suggest that the complexity of the pre-parent firm does not moderate the impact of cross-industry spinoffs on the forecast accuracy of the parent firm's close peers, relative to its distant peers. I do not find support for H2A. Columns 3 and 4 present the results for the forecast dispersion analysis. In Column 3, *Post×Peer* is positive and insignificant while in Column 4, *Post×Peer* is negative and significant at the 5% level (-0.083, t = -2.497).[19] The difference in the coefficient of *Post×Peer* in Columns 3 and 4 is significant at the 1% level (f-stat = 9.83, p-value = 0.0019), which suggests that the decrease in forecast dispersion after a cross-industry spinoff for close peers, relative to distant peers, is partially driven by the operational complexity of the pre-parent firm and the reduction in analysts' information processing costs.[20] Overall, I find support for H2B.

6.3.4 Same-Industry Spinoffs – Change in Industry Concentration

In this section, I examine whether the impact of same-industry spinoffs on the forecast accuracy and forecast dispersion of the parent firm's close peers, relative to its distant peers, are

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[19] Alternatively, in untabulated results, I create a continuous variable, *Complex_Cont* that equals the number of business segments in the pre-parent firm. I find consistent results.

[20] To calculate the f-stat, I create a binary variable, *Complex*, that equals 1 if the number of segments in the pre-parent firm is above the median number of segments, and 0 otherwise. I then test whether the sum of the coefficients of *Post×Complex* and *Post×Peer×Complex* is significantly different from zero.

moderated by changes in the peer firm's industry concentration. First, I estimate the following equation to examine the impact of same-industry spinoffs on the industry concentration of close peers, relative to distant peers.

$$HHI_{s,j,t} \quad = \quad \alpha + \beta_1 Post_t + \beta_2 Peer_{s,j} + \beta_3 Post{\times}Peer_{s,j,t} + \gamma Controls_{j,t} + \delta FE + \varepsilon_{s,j,t} \qquad (3)$$

The dependent variable, *HHI*, is the Herfindahl-Hirschman Index, which is measured as the sum of squared market share of a peer firm's annual net sales within the peer firm's four-digit SIC code. *HHI* is measured for each peer firm on an annual basis from the pre-spinoff to the post-spinoff period. The variable of interest is *Post×Peer*. If $\beta_3 < 0$, it suggests that close peers, relative to distant peers, operate in industries that become less concentrated after a same-industry spinoff. The regression controls for changes in industry concentration due to delisting and IPOs. It also includes fixed effects for each spinoff event, firm × event, and year-cohort, and cluster standard errors at the peer firm level. Table 14 presents the multivariate results using different regression specifications. Across all regression specifications, I find that *Post×Peer* is negative and significant at the 1% level, suggesting that close peers, relative to distant peers, operate in industries that become less concentrated after a same-industry spinoff.

Next, I examine whether the decrease in forecast accuracy and the increase in forecast dispersion after a same-industry spinoff for close peers, relative to distant peers, is moderated by changes in industry concentration. For each peer firm, I calculate the average *HHI* in the pre-spinoff and post-spinoff periods and split the sample based on whether the peer firm's HHI increased or decreased after the spinoff. Table 15 presents the multivariate results. Columns 1 and 2 present forecast accuracy analysis. In Column 1, *Post×Peer* is positive and insignificant, while in Column 2, *Post×Peer* is positive and significant at the 1% level (0.109, p-value = 4.068). The difference in the coefficient of *Post×Peer* in Columns 1 and 2 is significant at the 1% level (f-stat = 11.20, p-value = 0.0008).[21] These results suggest that the decrease in forecast accuracy for close peers, relative to distant peers, after a same-industry spinoff can be partially explained by a decrease in the industry concentration. I find support for H4A. Columns 3 and 4 present the results of the forecast dispersion analysis. In Column 3, *Post×Peer* is negative and insignificant, while in Column 4, *Post×Peer* is positive and significant at the 1% level (0.10, t-stat = 5.354). The difference in the coefficient of *Post×Peer* in Columns 3 and 4 is significant at the 1% level (f-stat = 17.91, p-value = 0.0000), suggesting that the increase in forecast dispersion for close peers, relative to distant peers, after a same-industry spinoff, is partially explained by the decrease in industry concentration. I find support for H4B. Overall, these results suggest that changes in industry composition due to a decrease in industry concentration can complicate the forecasting process for analysts.

6.3.5 Same-Industry Spinoffs – Volatility of Peer Firm Fundamentals

If same-industry spinoffs are disruptive events that affect industry conditions, it is plausible that close peers, relative to distant peers, experience greater cash flow and income volatility in the post-spinoff period. To test this possibility, I examine three measures of firm fundamentals. *Cash_Vol* is the standard deviation of the peer firm's operating cash flow for the previous four quarters. *OpInc_Vol* is the standard deviation of the peer firm's operating income before depreciation for the previous four quarters. *IncBefExtra_Vol* is the standard deviation of the peer firm's income before extraordinary items for the previous four quarters. First, I estimate the

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[21] To calculate the f-stat, I create a binary variable, *HHI_Inc*, that equals 1 if the HHI of the peer firm increased in the post-spinoff period, relative to the pre-spinoff period, and 0 otherwise. I then test whether the sum of the coefficients of *Post×HHI_Inc* and *Post×Peer×HHI_Inc* is significantly different from zero.

following equation to examine the impact of same-industry spinoffs on the cash flow and income volatility of close peers, relative to distant peers, comparing a six-quarter pre-spinoff period to a six-quarter post-spinoff period.

$$Vol_{s,j,t} \quad = \quad \alpha + \beta_1 Post_t + \beta_2 Peer_{s,j} + \beta_3 Post{\times}Peer_{s,j,t} + \gamma Controls_{j,t} + \delta FE + \varepsilon_{s,j,t} \qquad (4)$$

The dependent variable, *Vol*, represents one of three volatility measures: *Cash_Vol*, *OpInc_Vol* or *IncBefExtra_Vol*. The variable of interest is *Post×Peer*. If $\beta_3 > 0$, it suggests that after a same-industry spinoff, cash flow or income volatility is greater for close peers, relative to distant peers. The regression controls for peer firm characteristics including size (*Size*), leverage (*Leverage*) and market to book ratio (*MTB*). It also includes fixed effects for each spinoff event, firm × event, and quarter-cohort, and cluster standard errors at the peer firm level. Table 16 presents the multivariate results. In Column 1, *Post×Peer* is positive and insignificant, suggesting that after a same-industry spinoff, the change in cash flow volatility between close and distant peers is not statistically different. In Column 2, *Post×Peer* is positive and significant at the 1% level (21.632, t-stat = 3.330) and in Column 3, *Post×Peer* is positive and significant at the 5% level (15.997, t-stat = 2.380). These results suggest that after same-industry spinoff, income volatility increases for close peers, relative to distant peers.

Next, I examine whether the decrease in forecast accuracy and the increase in forecast dispersion after a same-industry spinoff is moderated by changes in the peer firm's cash flow and income volatility. I separate the sample based on whether the peer firm's cash flow or income volatility increased or decreased in the post-spinoff period, relative to the pre-spinoff period. Table 17, Panel A presents the multivariate results for operating cash flow volatility. Columns 1 and 2 present the forecast accuracy analysis. In Column 1, *Post×Peer* is positive and significant at the

1% level (0.110, t-stat = 4.695), while in Column 2, *Post×Peer* is positive and insignificant. The difference in the coefficient of *Post×Peer* between Columns 1 and 2 is significant at the 5% level, (f-stat = 4.09, p-value = 0.0434), suggesting that the decrease in forecast accuracy for close peers, relative to distant peers, after a same-industry spinoff is partially explained by an increase in cash flow volatility.[22] Columns 3 and 4 present the forecast dispersion results. In Column 3, *Post×Peer* is positive and significant at the 1% level (0.061, t-stat = 3.639), while in Column 4, *Post×Peer* is positive and significant at the 5% level (0.051, t-stat = 1.979). The difference in the coefficients of *Post×Peer* in Columns 3 and 4 is not significant, suggesting that the increase in forecast dispersion for close peers, relative to distant peers, after a same-industry spinoff is not explained by increase in cash flow volatility.

Table 17, Panel B presents the multivariate results for operating income volatility. Columns 1 and 2 present the forecast accuracy analysis. In Column 1, *Post×Peer* is positive and significant at the 1% level (0.104, t-stat = 4.466), while in Column 2, *Post×Peer* is positive and insignificant. The difference in the coefficient of *Post×Peer* in Columna 1 and 2 is not significant, suggesting that the decrease in forecast accuracy for close peers, relative to distant peers, after a same-industry spinoff is not explained by an increase in operating income volatility.[23] Columns 3 and 4 present the forecast dispersion analysis. In Column 3, *Post×Peer* is positive and significant at the 1% level (0.082, t-stat = 4.836), while in Column 4, *Post×Peer* is negative and insignificant. The difference in the coefficient of *Post×Peer* in Columns 3 and 4 is significant at the 1% level (f-stat = 10.90, t-stat = 0.001), suggesting that the increase in forecast dispersion for close peers, relative to distant

[22] To calculate the f-stat, I create a binary variable, *CF_Vol_Inc*, that equals 1 if *Cash_Vol* of the peer firms increased in the post-spinoff period, and 0 otherwise. I then test whether the sum of coefficients of *Post×CF_Vol_Inc* and *Post×Peer× CF_Vol_Inc* is significantly different from zero.

[23] To calculate the f-stat, I create a binary variable *Income_Vol_Inc*, that equals 1 if *Income_Vol* of the peer firms increased in the post-spinoff period and 0 otherwise. I then test whether the sum of coefficients of *Post×Income_Vol_Inc* and *Post×Peer×Income_Vol_Inc* is significantly different from zero.

peers, after the same-industry spinoff can be partially explained by an increase in operating income volatility.

Table 17, Panel C presents the multivariate results for income before extraordinary items volatility. Columns 1 and 2 present the forecast accuracy analysis. In Column1, *Post×Peer* is positive and significant at the 1% level (0.084, t-stat = 3.531), while in Column 2, *Post×Peer* is positive and significant at the 5% level. The difference in the coefficient of *Post×Peer* in Columns 1 and 2 is significant at the 10% level (f-stat = 3.33, p-value = 0.068), which provides weak evidence that the decrease in forecast accuracy for close peers, relative to distant peers, after a same-industry spinoff is partially explained by the increase in income before extraordinary income volatility.[24] Columns 3 and 4 present the results for the forecast dispersion analysis. In Column 3, *Post×Peer* is positive and significant at the 1% level (0.069, t-stat = 3.809), while in Column 4, *Post×Peer* is positive and insignificant. The difference in the coefficient of *Post×Peer* in Columns 3 and 4 is significant at the 1% level (f-stat = 6.66, p-value 0.01), suggesting that the increase in forecast dispersion of close peers, relative to distant peers, after a same-industry spinoff can be partially explained by an increase in volatility of income before extraordinary items. Overall, I find that same-industry spinoffs can be disruptive events that affect the volatility of peer firm fundamentals which subsequently leads to lower forecast accuracy and higher forecast dispersion.

6.3.6 Same-Industry Spinoffs – Incremental Segment Disclosures

In this section, I examine whether the decrease in forecast accuracy and increase in forecast dispersion after a same-industry spinoff are moderated by incremental segment disclosures from

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[24] To calculate the f-stat, I create a binary variable *IncBefExtra_Vol_Inc*, that equals 1 if *IncBefExtra _Vol* of the peer firms increased in the post-spinoff period and 0 otherwise. I then test whether the sum of coefficients of *Post×IncBefExtra_Vol_Inc* and *Post×Peer×IncBefExtra_Vol_Inc* is significantly different from zero.

the post-parent or spinoff firm. First, I examine whether the post-parent firm, relative to the pre-parent firm, provides incremental business segment disclosures. I manually compare the segment disclosures of the pre-parent firm before the initial filing date of the Form 10-12B and the segment disclosures of the post-parent firm after the spinoff effective date. In the post-spinoff period, the post-parent firm derecognizes the segment disclosures related to the operations of the spinoff firm and reports it as discontinued operations. If the segment disclosures of the post-parent firm only includes its remaining segments, the post-parent firm did not provide incremental disclosures. Incremental segment disclosures are provided if the post-parent firm discloses additional business segments or voluntarily redefines its segments to better reflect its remaining operations. Table 18 Columns 1 to 4 present the multivariate results. Columns 1 and 2 presents the forecast accuracy analysis. In Column 1, *Post*×*Peer* is positive and significant at the 1% level (0.094, t-stat = 3.946), while in Column 2, *Post*×*Peer* is positive and insignificant. The difference in the coefficient of *Post*×*Peer* in Columns 1 and 2 is not significant, suggesting that the decrease in forecast accuracy after a same-industry spinoff is not driven by incremental segment disclosures by the post-parent firm.[25] Columns 3 and 4 presents the forecast dispersion analysis. In Column 3, *Post*×*Peer* is positive and significant at the 1% level (0.069, t-stat = 4.002), while in Column 4, *Post*×*Peer* is negative and insignificant. The difference in the coefficient of *Post*×*Peer* in Columns 3 and 4 is significant at the 10% level (f-stat = 3.22, p-value = 0.073), providing weak evidence that the increase in forecast dispersion after a same-industry spinoff is driven by a lack of incremental segment disclosures by the post-parent firm.

[25] To calculate the f-stat, I create a binary variable, *Par_Seg_Inc*, that equals 1 if the post-parent firm provides incremental segment disclosures and 0 otherwise. I then test whether the sum of coefficients of *Post*×*Par_Seg_Inc* and *Post*×*Peer*× *Par_Seg_Inc* is statistically different from zero.

Second, I examine whether the spinoff firm, relative to the pre-parent firm, provides incremental segment disclosures about its operations. Since the spinoff firm operates in the same or related industry as the pre-parent firm, incremental segment disclosures by the spinoff firm can be relevant to the parent firm's close peers. I manually compare the segment disclosures of the pre-parent firm before the initial filing date of the Form 10-12B and those of the spinoff firm immediately after the spinoff effective date. For the segment disclosures of the pre-parent firm, I examine the number of reportable segments that comprise the operations of the spinoff firm. Incremental segment disclosures are provided if the spinoff firm discloses more reportable segments than the pre-parent's segment disclosures about the operations of the spinoff firm.

Table 18 Columns 5 to 8 present multivariate results. Columns 5 and 6 presents the forecast accuracy analysis. In Column 5, *Post×Peer* is positive and significant at the 1% level (0.094, t-stat = 4.023), while in Column 6, *Post×Peer* is negative and insignificant. The difference in the coefficient of *Post×Peer* in Columns 5 and 6 is significant at the 1 % level (f-stat = 11.70, p-value = 0.006), suggesting that the decrease in forecast accuracy of close peers, relative to distant peers, after a same-industry spinoff is driven by a lack of incremental segment disclosures by the spinoff firm. Columns 7 and 8 present the results for the forecast dispersion analysis. In Column 7, *Post×Peer* is positive and significant at the 1% level (0.057, t-stat = 3.372) while in Column 8, *Post×Peer* is positive and insignificant. The difference in the coefficient of *Post×Peer* in Columns 7 and 8 is significant at the 5% level (f-stat = 5.84, p-value = 0.0160), suggesting that the increase in forecast dispersion of close peers, relative to distant peers, after same-industry spinoff is driven by a lack of incremental segment disclosures by the spinoff firm. Overall, these results suggest that incremental segment disclosures by the spinoff firm, can mitigate the decrease in forecast accuracy and increase in forecast dispersion for close peers, relative to distant peers after a same-industry spinoff. I find some support for H5A and H5B.

Chapter 7: Additional Analyses

7.1 Information Uncertainty of Peer Firms in the Pre-Spinoff Period

In this section, I examine whether the main results are moderated by the level of information uncertainty of peer firms in the pre-spinoff period. For same-industry spinoffs, the decrease in forecast accuracy and forecast dispersion may be less pronounced for close peers with stronger information environments, as analysts may have a clearer understanding of how changes in industry conditions following the spinoff will affect peer firm earnings. In contrast, for cross-industry spinoffs, the decline in forecast dispersion may be more pronounced for close peers with weaker information environments. If the post-parent firm becomes less complex to cover, analysts may rely more heavily on the information produced by the post-parent firm when forecasting earnings for peers with weak information environments (Shroff, Verdi and Yost 2017). To measure the level of information uncertainty of peer firms in the pre-spinoff period, I use the average daily bid-ask spread for 180 days ending on the quarter before the initial filing date of the Form 10-12B.

Table 19, Columns 1 to 4 presents the multivariate results for cross-industry spinoffs. Columns 1 and 2 present the forecast accuracy analysis. *Post×Peer* is negative and insignificant in both columns. Columns 3 and 4 present the forecast dispersion analysis. In Column 3, *Post×Peer* is negative and insignificant, while in Column 4, *Post×Peer*, is negative and significant at the 5% level (-0.084, t-stat = -2.429). The difference in the coefficient of *Post×Peer* in Columns 3 and 4 is significant at the 5% level (f-stat = 3.91, p-value = 0.0486), suggesting that the decrease in forecast dispersion is more pronounced for close peers facing greater information uncertainty in the pre-spinoff period.[26]

[26] To calculate the f-stat, I create a binary variable, *Uncertain*, that equals 1 if the *Bid_Ask* for a peer firm is greater than the median, and 0 otherwise. I then test whether the sum of the coefficients of *Post×Uncertain* and *Post×Peer×Uncertain* is statistically different from zero.

Columns 5 to 8 presents the multivariate results for same-industry spinoffs. Columns 5 and 6 present the forecast accuracy analysis. In Column 5, *Post*×*Peer* is positive and insignificant, while in Column 6, *Post*×*Peer* is positive and significant at the 1% level (0.169, t-stat = 3.591). The difference in the coefficient of *Post*×*Peer* in Columns 5 and 6 is significant at the 1% level (f-stat = 25.99, p-value = 0.000), suggesting that the decrease in forecast accuracy for close peers, relative to distant peers, after a same-industry spinoff is driven by peer firms with greater information uncertainty. Columns 7 and 8 present the forecast dispersion analysis. In Column 7, *Post*×*Peer* is positive and insignificant while in Column 8, *Post*×*Peer* is positive and significant at the 1% level (0.08, t-stat = 3.680). The difference in the coefficient of *Post*×*Peer* in Columns 7 and 8 is significant at the 1% level (f-stat = 18.95, p-value = 0.000) which suggests that the increase in forecast dispersion for close peers, relative to distant peers, after a same-industry spinoff is driven by peer firms with greater information uncertainty in the pre-spinoff period.

Chapter 8: Robustness Tests

8.1 Parallel Trends Assumption

In this section, I assess the parallel trends assumption, which is an important criterion for using a difference-in-difference research design. The parallel trends assumption stipulates that, in the absence of the treatment, the treatment and control groups should exhibit similar changes in the dependent variable overtime. If the parallel trends assumption is satisfied, then post-treatment differences between the treatment and control group can be attributed to the treatment itself, rather than other confounding factors that affect the two groups differently.

I examine whether close and distant peers exhibit similar trends in forecast accuracy and forecast dispersion during the pre-spinoff period. If the pre-spinoff trends are comparable between the two groups, then any divergence observed in the post-spinoff period can be more credibly attributed to the spinoff. To assess the parallel trends assumption, I estimate Equation (5) for the forecast accuracy analysis and Equation (6) for the forecast dispersion analysis.

$$FError_{s,i,j,t} = \alpha + \beta_1 Period_t + \beta_2 Peer_{s,j} + \beta_3 Period \times Peer_{s,j,t} + \gamma Controls_{i,j,t} + \delta FE + \varepsilon_{s,i,j,t} \quad (5)$$

$$Disp_{s,j,t} = \alpha + \beta_1 Period_t + \beta_2 Peer_{s,j} + \beta_3 Period \times Peer_{s,j,t} + \gamma Controls_{i,j,t} + \delta FE + \varepsilon_{s,j,t} \quad (6)$$

Equations (5) and (6) follow the same specifications as Equations (1) and (2), respectively, in terms of the dependent variable, control variables, fixed effects and clustered standard errors. However, Equations (5) and (6) replace *Post* with *Period*, which is a set of 12 dummy variables that equals 1 for a given quarter in the pre-spinoff and post-spinoff periods, and 0 otherwise.[27] The

[27] For example, *Period1* is dummy variable that equals 1 for the first quarter in the pre-spinoff period and 0 otherwise. *Period7* is a dummy variable that equals 1 for the first quarter in the post-spinoff period and 0 otherwise.

variable of interest is *Period×Peer*. The coefficient on these interaction terms reflects the difference in forecast accuracy or forecast dispersion between close and distant peers in each period. If the interaction terms are insignificant in the pre-spinoff period, the parallel trends assumption is met.

Table 20 presents the multivariate results using Period 6, the final quarter in the pre-spinoff period, as the reference period. Across Columns 1 to 4, *Period×Peer* is insignificant in the pre-spinoff period from Periods 1 to 6, consistent with the parallel trends assumption. Figures 4 and 5 present coefficient plots of *Period×Peer* for cross-industry and same-industry spinoffs, respectively, in the forecast accuracy analysis. Figures 6 and 7 present the corresponding coefficient plots for the forecast dispersion analysis. These figures suggest that the divergence in analyst forecast properties observed in the post-spinoff period between close and distant peers can be more credibly attributed to the spinoff.

8.2 Entropy Balancing

In this section, I use entropy balancing to address the concern that the main results are driven by observable differences between close and distant peers. Entropy balancing reweights the distant peers such that the weighted first, second and third moments of their covariates match those of the close peers (Hainmueller 2012; Hainmueller and Xu 2013). Table 21 presents the descriptives for the covariates used in the forecast accuracy analysis, before and after reweighting. Panel A presents the results for cross-industry spinoffs, while Panel B presents the results for same-industry spinoffs.[28] After reweighting, the covariates between close and distant peers are well

[28] In untabulated results, I perform entropy balancing for cross-industry and same-industry spinoffs in the forecast dispersion analysis. Entropy balancing achieved covariate balance between close and distant peers across the first three moments.

balanced across the first three moments, mitigating concerns about differences in observable characteristics.

Table 22 presents the multivariate results using the reweighted distant peers. Columns 1 and 3 present the results for cross-industry spinoffs. In Column 1, *Post×Peer* is negative and insignificant, while in Column 3, *Post×Peer* is negative and significant at the 1% level (-0.062, t-stat = -3.016), which is consistent with the main results. Columns 2 and 4 present the results for same-industry spinoffs. In both columns, *Post×Peer* is positive and insignificant, representing a weaker effect relative to the main results. One possible explanation for the weaker results is the relatively small number of close peers compared to distant peers.[29] To achieve covariate balance, entropy balancing may assign disproportionally high weights to more comparable distant peers that drive the regression results while assigning very low weights to the remaining of the control group.[30]

8.3 Alternative Definitions of Peer Firms Using SIC Codes

In the main analysis, peer firms that share the same three-digit SIC code but different four-digit SIC code as the pre-parent firm were excluded to distinguish between close and distant peers. In this section, I reexamine the main results by including these previously excluded peer firms into the analysis. First, I expand the definition of distant peers to include these excluded peer firms, such that distant peers comprise of firms with the same two-digit SIC code but different four-digit

[29] Refer to Tables 5 and 6 for the number of close and distant peers for each spinoff.
[30] Within the forecast accuracy analysis, same-industry spinoff and distant peers sample, I examine the distribution of _webal, which is the variable assigned to the entropy balancing weights. The min, median, mean and max of _webal is 0.01, 0.18, 0.35, 6.97.

SIC code. Table 23, Columns 1 to 4 present the multivariate results. The findings are consistent with the main result for the forecast accuracy and forecast dispersion analyses.

Next, I expand the definition of close peers to include the previously excluded peer firms, redefining close peers as those that share at least the same three-digit SIC code. Columns 5 to 8 present the multivariate results. I find weaker results for the forecast accuracy and forecast dispersion analyses. These results suggests that the spillover effects of spinoffs are not pervasive and limited to firms with the same four-digit SIC code as the pre-parent firm.

8.4 Defining Close and Peer Firms Using NAICS Codes

In this section, I examine the robustness of the main results by using an alternative industry classification scheme to define the parent firm's close and distant peers. The NAICS was jointly developed by the federal statistical agencies of Canada, Mexico and the U.S. in 1999 to replace SIC codes. NAICS uses a six-digit code within a production-based framework to classify firms.[31]

Using NAICS codes, close peers operate in the same industry as the pre-parent firm and share the same five-digit NAICS code as the pre-parent firm in the year before the initial filing date of the Form 10-12B. Distant peers share the same three-digit NAICS code but different four-digit NAICS code as the pre-parent firm. Distant peers operate in the same subsector, but not in the same industry group. [32] Table 24 presents the multivariate results. In Columns 2 and 4, I find

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[31] The first two digits of the NAICS code represents the sector, the third digit represents the subsector, the fourth digit represents the industry group, the fifth digit represents the industry, and the sixth digit designates a national industry.
[32] The NAICS-based definitions are aligned with the SIC-based definitions used in the main analysis to ensure consistency. First, I define distant peers as firms that share the same three-digit NAICS code, rather than the broader two-digit NAICS code, to limit the inclusion dissimilar distant peers. Second, I differentiate between close and distant peers by excluding firms that share the same four-digit NAICS code but different five-digit NAICS code as the pre-parent firm. These classification choices yield a sample of close and distant peers that is comparable to the sample used in the main analysis.

consistent results that forecast accuracy decreases and forecast dispersion increases for close peers, relative to distant peers, after a same-industry spinoff. Columns 1 and 3 present the results for cross-industry spinoffs. In Column 3, *Post×Peer* is negative and insignificant, suggesting that forecast dispersion is not statistically different between close and distant peers after a cross-industry spinoff. This result is much weaker than the main analysis. Overall, the spillover effects of same-industry spinoffs are consistent across NAICS and SIC codes. However, I find weaker results on the impact of cross-industry spinoffs on the forecast dispersion of close peers using NAICS codes, than SIC codes.

Chapter 9: Conclusion

In conclusion, this thesis examines how cross-industry and same-industry spinoffs affect the forecast accuracy and forecast dispersion of the parent firm's close peers. Following a cross-industry spinoff, I find that forecast dispersion decreases for close peers, particularly for pre-parent firms that are operationally complex. This finding suggests that the separation of unrelated operations can reduce the complexity of the post-parent firm and reduce the analysts' information processing costs, which helps facilitate information spillovers between the parent firm and its close peers. In contrast, following a same-industry spinoff, I find that forecast accuracy decreases and forecast dispersion increases for close peers relative to distant peers. These results are more pronounced when close peers, relative to distant peers, operate in industries that become less concentrated in the post-spinoff period and those that have higher cash flow or income volatility in the post-spinoff period. These findings suggest that same-industry spinoffs are disruptive industry events that complicate the forecasting process as analysts assess how close peers adapt to changes in industry composition. Moreover, these disruptions outweigh the potential informational benefits associated with spinoff firm's initial financial statements. Overall, the main analysis demonstrates the importance of distinguishing between cross-industry and same-industry spinoffs when examining the spillover effects of spinoffs on the analyst forecast properties of the parent firm's close peers.

This thesis offers several contributions. First, it extends the spinoff literature, which has primarily focused on the direct effects of spinoffs on the parent and spinoff firms. By examining the impact of spinoffs on the analyst forecast properties of the parent firm's close peers, this thesis contributes to an emerging stream of research that explores the broader implications of spinoffs (Kim and Suh 2023; Kim, Kim, Rosano and Suh 2025). Second, this thesis identifies two additional mechanisms that help explain the observed changes in forecast accuracy and forecast dispersion of the parent firm's close peers. While recent studies focus on the informational value of spinoffs by examining whether the spinoff firm was previously disclosed as a reportable segment by the pre-parent firm (Kim and Suh 2023; Kim, Kim, Rosano and Suh 2025), this thesis demonstrates that (1) cross-industry spinoffs can reduce a firm's operational complexity and thereby reduce the analysts' information processing costs of following that firm (2) same-industry spinoffs can be disruptive events that change industry composition and complicate the forecasting process. Finally, this thesis contributes to a growing body of research that views corporate restructurings as industry-wide events with broader spillover effects (Brown, Byard, Darrough and Suh 2024; Kim and Suh 2023; Kim, Kim, Rosano and Suh 2025; Hinson and Piao 2025). While prior studies find that corporate restructurings that increase (decrease) public information can improve (deteriorate) the information environment of close peers, this thesis finds that the informational benefits of same-industry spinoffs can be overshadowed by heightened uncertainty due to changes in industry composition. Future research can build on these findings by exploring how spinoffs and other forms of divestitures influence the disclosure quality, investment efficiency and strategic behaviour of peer firms.

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Appendix: Variable Definitions

Analyst_Follow	Equals the number of unique analysts that made a quarterly EPS forecast for a peer firm in a quarter.
Bid_Ask	Equals the daily bid-ask spread, scaled by the average bid-ask spread for 180 days ending the quarter before the initial filing date of the Form 10-12B.
Broker Size	Equals the number of analysts employed by a brokerage in a calendar quarter.
Cash_Vol	Equals the standard deviation of quarterly operating cash flow for the previous four quarters.
CF_Vol_Inc	Equals 1 if *Cash_Vol* for the peer firm increased in the post-spinoff period. Equals 0 if *Cash_Vol* decreased in the post-spinoff period.
Complex_Cont	Equals the number of business segments in the pre-parent firm.
Delist	Equals 1 for six quarters after the quarter of the final financial report by the delisting firm, and 0 otherwise.
Disp	Equals the standard deviation of the most recent quarterly EPS forecast within 90 days before the earnings announcement date, scaled by the peer firm's stock price at the beginning of the quarter, times 100.
FError	Equals the absolute difference between the most recent quarterly EPS forecast within 90 days before the earnings announcement date, and the actual quarterly EPS, scaled by the peer firm's stock price at the beginning of the quarter, times 100.
Firm_Exp	Equals the number of quarters an analyst makes a quarterly EPS forecast for a firm before the forecast date.
Gen_Exp	Equals the number of calendar quarters an analyst appears in IBES before the forecast date.
IncBefExtra_Vol	Equals the standard deviation of quarterly income before extraordinary items for the previous four quarters.
OpInc_Vol	Equals the standard deviation of quarterly operating income for the previous four quarters.
IPO	Equals 1 for the quarter of the initial financial report issued by an IPO firm after the IPO date, and 0 otherwise.
SIC2_Count	Equals the number of unique 2-digit SIC codes in an analyst's portfolio for a calendar quarter.
HHI	Equals the sum of each firm's squared proportion of their net annual sales within a four-digit SIC code industry.
HHI_Inc	Equals 1 if HHI of the peer firm increases in the post-spinoff period. Equals 0 if HHI of the peer firm decreases in the post spinoff period.
Horizon	Equals the number of days between the forecast date and the earnings announcement date.
Leverage	Equals the total liabilities scaled by total assets in the prior quarter.
Loss	Equals 1 if income before extraordinary items is negative in the prior quarter, and 0 otherwise.
MTB	Equals the total market value of equity scaled by the book value of equity in the prior quarter.
Peer	Equals 1 if the peer firm has the same 4-digit SIC code as the pre-parent firm in the year before the initial filing date of the Form 10-12B. Equals 0 if the peer

	firm has the same 2-digit but different 3-digit SIC code as the pre-parent firm in the year before the initial filing date of the Form 10-12B.
Period	Equals 1 to 6 for the six quarters before the initial filing date of Form 10-12B or 7 to 12 for the six quarters after the initial financial report by the post-parent firm after the spinoff effective date.
Port Size	Equals the number of EPS forecasts an analyst provides for unique firms in a calendar quarter.
Post	Equals 1 for six quarters following the initial filing date of a financial report by the post-parent firm after the spinoff effective date. Equals 0 for the six quarters preceding the initial filing date of Form 10-12B.
Ret_Vol	Equals the standard deviation of monthly stock returns throughout the year preceding the forecast.
ROA	Equals the income before extraordinary items scaled by total assets in the prior quarter.
Size	Equals the natural log of total assets in the prior quarter.
Uncertain	Equals 1 if *Bid_Ask* for a peer firm is greater than the median, and 0 otherwise.

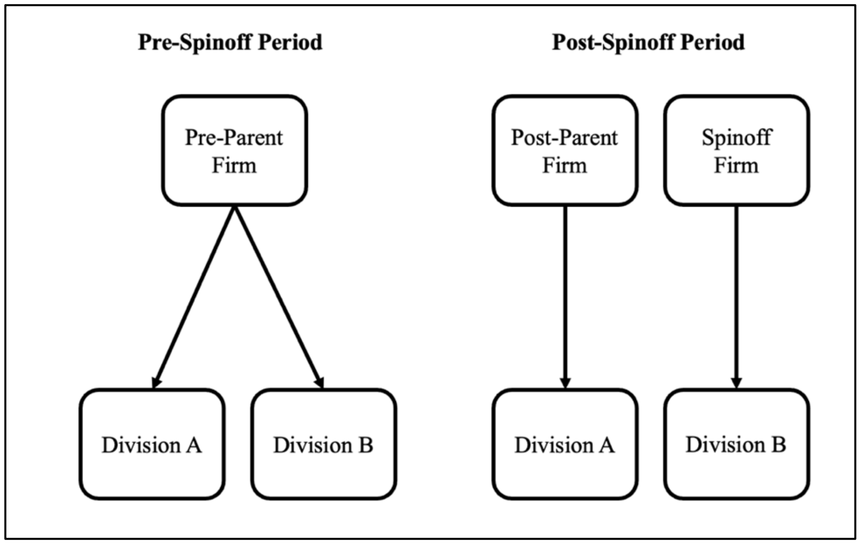

Figure 1: Spinoff

This figure presents the firms and divisions involved in a spinoff. In the pre-spinoff period, the pre-parent firm operates Divisions A and B. The pre-parent firm announces its intention to spinoff Division B into a separate and independent spinoff firm. In the post-spinoff period, the spinoff firm operates Division B while the post-parent firm operates Division A.

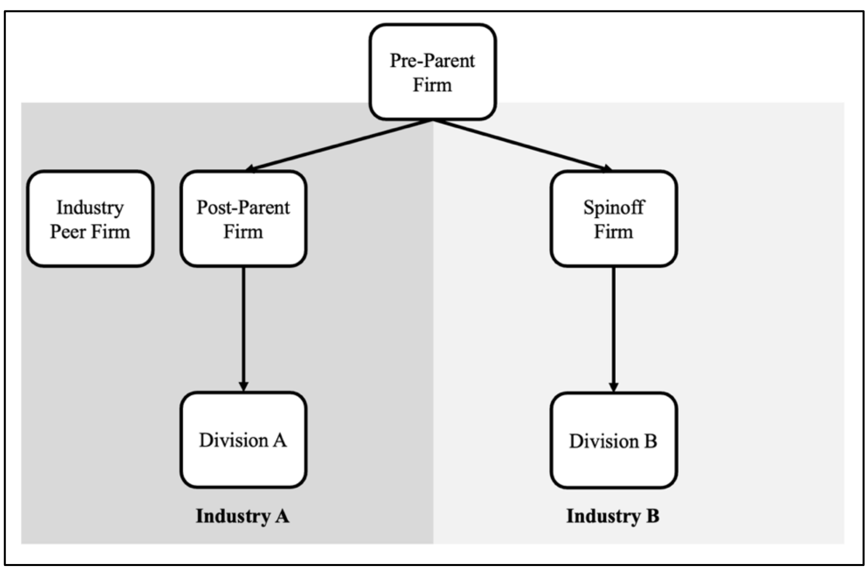

Figure 2: Cross-Industry Spinoff

This figure presents the firms and divisions involved in a cross-industry spinoff. The pre-parent firm announces its intention to spinoff Division B into a separate and independent spinoff firm. In the post-spinoff period, the post-parent and spinoff firms operate in two unrelated industries. The spinoff firm operates Division B while the post-parent firm operates Division A.

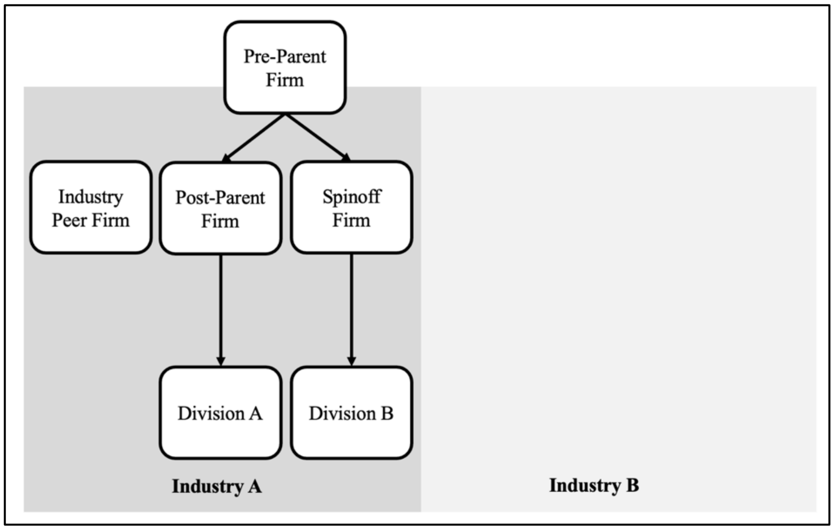

Figure 3: Same-Industry Spinoff

This figure presents the firms and divisions involved in a same-industry spinoff. The pre-parent firm announces its intention to spinoff Division B into a separate and independent spinoff firm. In the post-spinoff period, the post-parent and spinoff firms operate in the same or related industries. The spinoff firm operates Division B while the post-parent firm operates Division A.

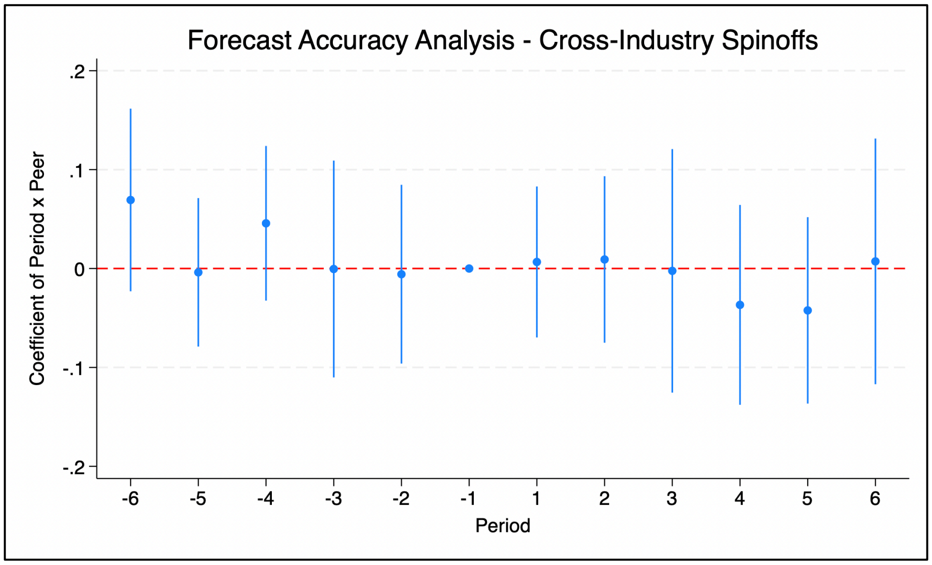

Figure 4: Coefficient Plot – Forecast Accuracy Analysis for Cross-Industry Spinoffs

This figure presents the coefficient plot of Equation 5 for cross-industry spinoffs in the forecast accuracy analysis. The dependent variable, *FError*, is the absolute difference between the most recent quarterly EPS forecast for the next fiscal quarter and the actual quarterly EPS, scaled by the stock price at the beginning of the quarter, times 100. *Period* is a set of dummy variables that equals 1 for a particular quarter in the pre-spinoff and post-spinoff periods and 0 otherwise. *Peer* equals 1 for close peers and 0 for distant peers.

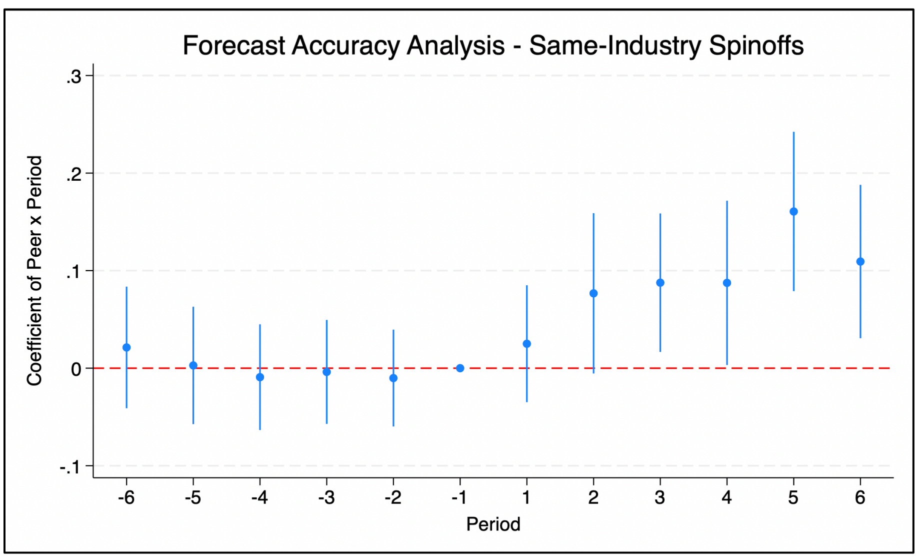

Figure 5: Coefficient Plot – Forecast Accuracy Analysis for Same-Industry Spinoffs

This figure presents the coefficient plot of Equation 5 for same-industry spinoffs in the forecast accuracy analysis. The dependent variable, *FError*, is the absolute difference between the most recent quarterly EPS forecast for the next fiscal quarter and the actual quarterly EPS, scaled by the stock price at the beginning of the quarter, times 100. *Period* is a set of dummy variables that equals 1 for a particular quarter in the pre-spinoff and post-spinoff periods and 0 otherwise. *Peer* equals 1 for close peers and 0 for distant peers.

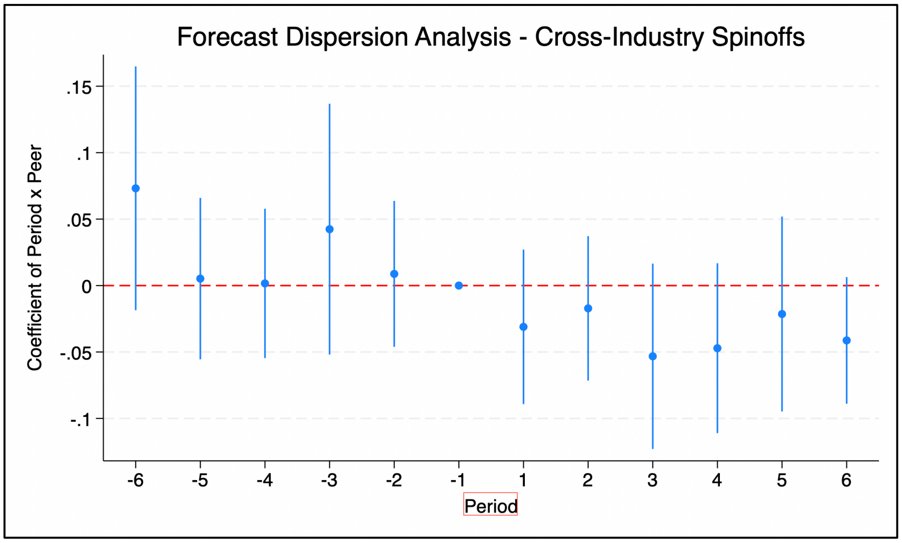

Figure 6: Coefficient Plot – Forecast Dispersion Analysis for Cross-Industry Spinoffs

This figure presents the coefficient plot of Equation 6 for cross-industry spinoffs in the forecast dispersion analysis. *Disp* is the standard deviation of the most recent quarterly EPS forecast, scaled by the stock price at the beginning of the quarter, times 100. *Period* is a set of dummy variables that equals 1 for a particular quarter in the pre-spinoff and post-spinoff periods and 0 otherwise. *Peer* equals 1 for close peers and 0 for distant peers.

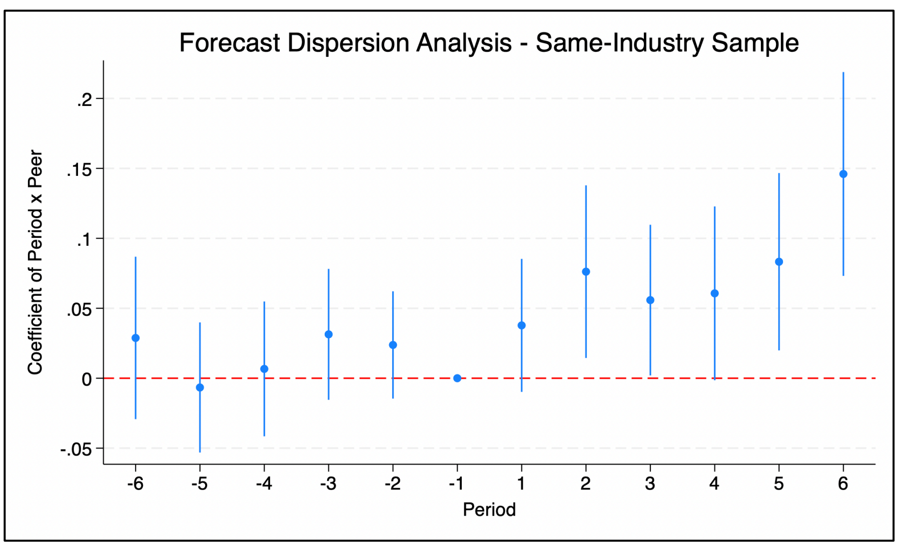

Figure 7: Coefficient Plot – Forecast Dispersion Analysis for Same-Industry Spinoffs

This figure presents the coefficient plot of Equation 6 for same-industry spinoffs in the forecast dispersion analysis. *Disp* is the standard deviation of the most recent quarterly EPS forecast, scaled by the stock price at the beginning of the quarter, times 100. *Period* is a set of dummy variables that equals 1 for a particular quarter in the pre-spinoff and post-spinoff periods and 0 otherwise. *Peer* equals 1 for close peers and 0 for distant peers.

Table 1: Sample Selection

Panel A: Number of Spinoffs		**Spinoffs**
	Unique Form 10-12B filings from 2010 to 2018	244
Less:	Unrelated share registrations and misclassified filings	187
Less:	Spinoffs with concurrent M&A and bankruptcy proceedings	159
Less:	Spinoff firms that did not file reports or filed reports before the initial Form 10-12B	126
Less:	Spinoff and parent firms that do not match Compustat or CRSP	118
Less:	Parent firms that are acquired immediately after the spinoff	114
Less:	Parent firms that are foreign issuers	113
Less:	Parent and spinoff firms that filed limited reports	110
Less:	Spinoffs without at least one close and distant peer	76

Panel B: Forecast Accuracy Analysis		**Firms**	**Forecasts**
	Close and distant peers	21,033	-
Less:	Firms that don't match CRSP or IBES	13,739	-
Less:	Firms that don't file a financial report before the initial Form 10-12B.	11,070	-
Less:	Firms that file less than three reports in the pre-spinoff and post-spinoff periods	10,223	-
Less:	Firms with missing information	9,478	534,352
Less:	Firms with analysts who provide fewer than three forecasts in the pre-spinoff and post-spinoff periods	5,327	196,835
Less:	Spinoffs without at least one close and distant peer	5,035	183,383

Panel C: Forecast Dispersion Analysis		**Firms**	**Firm Quarters**
	Firm quarters based on the forecast accuracy analysis	4,936	48,194
Less:	Firm quarters with missing forecast dispersion measures	2,832	24,917
Less:	Firms that do not have forecast dispersion observations in the pre-spinoff and post-spinoff periods.	2,826	24,907
Less:	Spinoffs without at least one close and distant peer	2,153	23,778

This table presents the sample selection process. Panel A presents the sample of spinoffs. Panel B presents the sample for the forecast accuracy analysis. The sample is compiled at the spinoff-peer firm-analyst-quarter level. Panel C presents the sample for the forecast dispersion analysis. The sample is compiled at the spinoff-peer firm-quarter level.

Table 2: Descriptive – Spinoffs Per Year

Year of the Effective Date	Cross-Industry Spinoffs	Same-Industry Spinoffs	Frequency	Percent (%)
2010	0	1	1	1.32%
2011	3	3	6	7.89%
2012	4	2	6	7.89%
2013	7	3	10	13.16%
2014	8	7	15	19.74%
2015	5	8	13	17.11%
2016	2	10	12	15.79%
2017	2	4	6	7.89%
2018	3	3	6	7.89%
2019	1	0	1	1.32%
Total	35	41	76	100%

This table presents the total number of spinoffs, cross-industry spinoffs, and same-industry spinoffs by the year of the effective date.

Table 3: Descriptive – Pre-Parent Firm Industry

SIC	Industry Description	Freq.
35	Industrial and Commercial Machinery and Transportation Equipment	13
28	Chemicals and Allied Products	10
38	Measuring, Analyzing and Controlling Instruments	9
73	Business Services	6
36	Electronic and Other Electrical Equipment and Components	5
29	Petroleum and Miscellaneous Plastics Products	4
37	Transportation Equipment	4
48	Communications	4
13	Oil and Gas Extraction	3
27	Printing, Publishing and Allied Industries	3
49	Electric, Gas and Sanitary Services	3
20	Food and Kindred Products	2
25	Furniture and Fixtures	2
44	Water Transportation	2
26	Paper and Allied Products	1
34	Fabricated Metal Products, Except Machinery and Transportation Equipment	1
59	Miscellaneous Retail	1
79	Amusement and Recreation Services	1
80	Health Services	1
87	Legal Services	1
	Total	76

This table presents the industry of the pre-parent firm. Industry is defined at the two-digit SIC level.

Table 4: Descriptive – Parent and Spinoff Firms

Panel A: Pre-parent firm at the fiscal year-end before the filing date of the Form 10-12B		
	Mean (millions)	Median (millions)
Assets	20,085	10,946
Revenue	16,268	7,967
Market Value	18,048	9,187

Panel B: Post-parent firm at the immediate fiscal year-end after the spinoff effective date		
	Mean (millions)	Median (millions)
Assets	15,373	7,485
Revenue	10,565	4,345
Market Value	15,230	6,134

Panel C: Spinoff firm at the immediate fiscal year-end after the spinoff effective date		
	Mean (millions)	Median (millions)
Assets	6,184	2,365
Revenue	6,885	1,835
Market Value	5,968	2,105

This table present the descriptive statistics of the pre-parent firm before the filing date of the 10-12b form, the post-parent firm at the immediate fiscal year-end after the spinoff effective date, and the spinoff firm at the immediate fiscal year-end after the spinoff effective date.

Table 5: Descriptive – Number of Peer Firms – Forecast Accuracy Analysis

Parent & Spinoff CIK	Close Peer	Distant Peer	Parent & Spinoff CIK	Close Peer	Distant Peer
859598 1690334	1	6	1328571 1520744	7	30
39899 1635718	1	9	4281 1675149	7	42
1469372 1636519	1	13	1039101 1544229	7	102
23217 1679273	1	37	1065088 1633917	8	21
103730 1487952	1	51	39899 1683606	8	28
1466258 1579241	1	79	1121484 1590584	8	70
29669 1669811	2	10	912093 1633978	9	60
29669 1669812	2	10	107263 1518832	9	64
833444 1546640	2	11	1389050 1635881	9	69
1105705 1591517	2	44	1021860 1599617	9	72
1111711 1629995	2	51	1045309 1644440	9	159
47217 1645590	2	70	1035002 1562039	10	2
98362 1598428	2	72	68505 1495569	10	104
30554 1627223	2	115	1163165 1534701	11	2
859598 1525221	3	6	717423 1573516	11	4
861361 1617898	3	12	1090872 1601046	11	53
1308161 1564708	3	40	101778 1510295	12	2
99780 1739445	3	56	1521332 1707092	13	28
29905 1587523	3	77	1385187 1567892	13	48
61986 1650962	3	77	1895262 1594590	13	72
29905 1723089	3	80	8670 1609702	14	39
1108109 1650445	4	16	1123494 1563665	14	62
1103982 1545158	4	36	1114483 1648893	15	41
313616 1659166	4	50	203527 1681622	16	43
1486957 1630805	4	80	1034670 1733186	19	26
1460329 1720116	5	14	1336920 1571123	21	38
789073 1519751	5	15	1770450 1677703	21	39
55772 1606757	5	39	10456 1620546	28	52
917520 1637761	5	41	1800 1551152	38	54
216228 1524471	5	86	1080014 1583107	41	53
216228 1524472	5	86	1365038 1589094	48	39
1096752 1632790	5	95	1142701 1575360	51	38
1395942 1745041	5	162	1623595 1532750	62	24
55785 1606498	6	14	876343 1642380	66	53
1039684 1587732	6	59	797468 1609253	71	23
77360 1720635	6	72	1367644 1671584	71	52
88205 1641991	6	74	875045 1681689	83	54
2969 1660690	6	146	876343 1708599	105	56
			Total	1,107	3,928

This table presents the number of close and distant peers for each spinoff in the forecast accuracy analysis.

Table 6: Descriptive – Number of Peer Firms – Forecast Dispersion Analysis

Parent and Spinoff CIK	Close Peer	Distant Peer	Parent and Spinoff CIK	Close Peer	Distant Peer
1469372 1636519	1	7	216228 1524471	4	51
23217 1679273	1	27	216228 1524472	4	51
313616 1659166	1	27	1395942 1745041	4	97
99780 1739445	1	33	1328571 1520744	5	16
47217 1645590	1	38	77360 1720635	5	36
1466258 1579241	1	49	912093 1633978	5	36
1096752 1632790	1	54	1389050 1635881	5	37
30554 1627223	1	58	88205 1641991	5	40
861361 1617898	2	5	68505 1495569	5	57
859598 1525221	2	6	1045309 1644440	5	82
833444 1546640	2	7	8670 1609702	6	20
55785 1606498	2	8	4281 1675149	6	28
1460329 1720116	2	10	1039684 1587732	6	41
1065088 1633917	2	14	1121484 1590584	6	44
1308161 1564708	2	20	1114483 1648893	7	21
1105705 1591517	2	22	1385187 1567892	7	28
29905 1723089	2	38	1021860 1599617	7	44
61986 1650962	2	43	10456 1620546	8	33
1486957 1630805	2	48	1336920 1571123	9	18
29905 1587523	2	49	107263 1518832	9	43
2969 1660690	2	71	717423 1573516	10	1
789073 1519751	3	8	1035002 1562039	10	2
55772 1606757	3	21	1521332 1707092	10	18
1103982 1545158	3	23	203527 1681622	11	24
1039101 1544229	3	53	1123494 1563665	12	36
1108109 1650445	4	8	1895262 1594590	12	66
39899 1683606	4	19	1034670 1733186	13	18
917520 1637761	4	20	1770450 1677703	14	19
1090872 1601046	4	30	1080014 1583107	18	40
			Total	290	1,863

This table presents the number of close and distant peers for each spinoff in the forecast dispersion analysis.

Table 7: Descriptive – Peer Firms

Panel A: Forecast Accuracy Analysis

	N	Mean	Median	Min	Max	Std Dev
FError	183,383	0.36	0.13	0.00	5.49	0.75
Analyst_Follow	183,383	13.00	12.00	1.00	34.00	7.72
Broker_Size	183,383	47.75	44.00	2.00	108.00	30.97
Delist	183,383	0.67	1.00	0.00	1.00	0.47
Firm_Exp	183,383	15.84	13.00	0.00	55.00	11.75
Gen_Exp	183,383	39.41	37.00	3.00	103.00	22.51
SIC2_Count	183,383	3.24	3.00	1.00	9.00	1.97
HHI	183,383	0.22	0.17	0.03	0.92	0.18
Horizon	183,383	49.55	49.00	1.00	90.00	32.46
IPO	183,383	0.14	0.00	0.00	1.00	0.35
Leverage	183,383	0.56	0.56	0.09	1.18	0.21
Loss	183,383	0.21	0.00	0.00	1.00	0.41
MTB	183,383	4.36	2.71	-20.28	58.22	8.09
Port_Size	183,383	13.87	13.00	2.00	34.00	6.32
Ret_Vol	183,383	0.09	0.08	0.03	0.28	0.05
ROA	183,383	0.01	0.01	-0.21	0.08	0.04
Size	183,383	8.56	8.63	4.42	12.33	1.70

Panel B: Forecast Dispersion Analysis

	N	Mean	Median	Min	Max	Std Dev
Disp	23,778	0.18	0.07	0.00	2.69	0.36
Analyst_Follow	23,778	12.14	11.00	3.00	33.00	6.33
Delist	23,778	0.65	1.00	0.00	1.00	0.48
HHI	23,778	0.23	0.19	0.04	0.93	0.18
IPO	23,778	0.13	0.00	0.00	1.00	0.34
Leverage	23,778	0.57	0.57	0.10	1.16	0.21
Loss	23,778	0.20	0.00	0.00	1.00	0.40
MTB	23,778	4.68	2.82	-23.32	63.86	9.02
Ret_Vol	23,778	0.09	0.08	0.03	0.25	0.05
ROA	23,778	0.01	0.01	-0.18	0.08	0.04
Size	23,778	8.55	8.50	4.85	12.14	1.55

This table presents the number of observations, mean, median, minimum, maximum and standard deviation of the dependent and control variables of the forecast accuracy and forecast dispersion analyses. All continuous variables are winsorized at the 1% and 99% levels. Variable definitions are in the appendix.

Table 8: Univariate Results

Panel A: Forecast Accuracy Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) *FError*																		
(2) *Post*	0.04*																	
(3) *Peer*	0.09*	0.00																
(4) *Analyst_Follow*	-0.13*	0.02*	0.12*															
(5) *Broker_Size*	-0.06*	0.01*	-0.01*	0.02*														
(6) *Delist*	0.04*	0.02*	0.22*	0.16*	-0.04*													
(7) *Firm_Exp*	-0.06*	0.24*	-0.04*	0.11*	0.08*	-0.06*												
(8) *Gen_Exp*	-0.04*	0.17*	-0.08*	-0.04*	0.07*	-0.06*	0.55*											
(9) *HHI*	-0.10*	0.02*	-0.30*	-0.19*	-0.03*	-0.35*	0.01*	0.10*										
(10) *Horizon*	0.01*	0.01*	-0.10*	-0.14*	-0.08*	-0.04*	-0.06*	0.10*	0.19*									
(11) *IPO*	0.07*	-0.02*	0.30*	0.03*	-0.02*	0.28*	-0.09*	-0.05*	-0.22*	-0.01*								
(12) *Leverage*	0.09*	0.06*	-0.07*	-0.03*	0.11*	-0.17*	0.13*	0.08*	0.03*	-0.11*	-0.14*							
(13) *Loss*	0.30*	0.07*	0.13*	-0.06*	-0.07*	0.14*	-0.08*	-0.02*	-0.11*	0.04*	0.18*	0.00						
(14) *MTB*	-0.08*	0.00	-0.01*	-0.03*	0.03*	-0.02*	-0.02*	0.03*	0.08*	0.02*	0.07*	0.16*	0.00					
(15) *Port*	0.02*	0.08*	0.10*	0.14*	0.23*	0.04*	0.17*	0.17*	-0.15*	-0.13*	0.01*	0.09*	0.03*	-0.04*				
(16) *Ret_Vol*	0.39*	0.04*	0.15*	-0.11*	-0.14*	0.12*	-0.16*	-0.08*	-0.09*	0.05*	0.19*	-0.07*	0.42*	-0.05*	-0.02*			
(17) *ROA*	-0.31*	-0.07*	-0.15*	0.10*	0.08*	-0.12*	0.08*	0.03*	0.12*	-0.04*	-0.22*	-0.04*	-0.67*	0.03*	-0.05*	-0.43*		
(18) *SIC2_Count*	-0.05*	0.03*	-0.19*	-0.16*	0.06*	-0.30*	0.03*	0.13*	0.34*	0.12*	-0.25*	0.07*	-0.13*	0.00	0.25*	-0.11*	0.14*	
(19) *Size*	-0.21*	0.05*	-0.03*	0.48*	0.21*	-0.07*	0.30*	0.05*	-0.08*	-0.24*	-0.14*	0.29*	-0.30*	-0.05*	0.11*	-0.48*	0.31*	-0.05*

Panel B: Forecast Dispersion Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) *Disp*																		
(2) *Post*	0.04*																	
(3) *Peer*	0.12*	0.00																
(4) *Analyst_Follow*	-0.06*	0.02	0.11*															
(5) *Delist*	0.05*	0.01	0.22*	0.15*														
(6) *HHI*	-0.14*	0.02*	-0.28*	-0.15*	-0.36*													
(7) *IPO*	0.06*	-0.02*	0.30*	0.06*	0.28*	-0.23*												
(8) *Leverage*	0.14*	0.06*	-0.07*	-0.07*	-0.18*	0.02*	-0.13*											
(9) *Loss*	0.32*	0.06*	0.12*	-0.02*	0.14*	-0.12*	0.17*	0.01										
(10) *MTB*	-0.07*	0.00	-0.01	-0.01	-0.02*	0.07*	0.06*	0.16*	0.01									
(11) *Ret_Vol*	0.42*	0.03*	0.15*	-0.05*	0.12*	-0.10*	0.16*	-0.07*	0.40*	-0.06*								
(12) *ROA*	-0.33*	-0.06*	-0.15*	0.05*	-0.12*	0.12*	-0.19*	-0.04*	-0.68*	0.04*	-0.39*							
(13) *Size*	-0.16*	0.05*	-0.05*	0.37*	-0.08*	-0.03*	-0.10*	0.31*	-0.28*	-0.05*	-0.45*	0.26*						

This table presents the univariate results for the dependent and control variables. Panel A presents the forecast accuracy analysis and Panel B presents the forecast dispersion analysis. * indicates that the correlation is significant at the 1% level. Continuous variables are winsorized at the 1% and 99% levels. Variable definitions are in the appendix.

Table 9: Cross-Industry Spinoffs on the Forecast Accuracy of Peer Firms

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent	*FError*	*FError*	*FError*	*FError*	*FError*	*FError*
Post	-0.002	-0.002	-0.002	-0.024	-0.023	
	(-0.424)	(-0.178)	(-0.182)	(-1.199)	(-1.194)	
Peer	0.085***	0.085**	0.055	0.041		
	(9.670)	(2.527)	(1.414)	(1.103)		
Post×Peer	-0.015	-0.015	-0.018	-0.020	-0.024	-0.025
	(-1.249)	(-0.559)	(-0.675)	(-0.713)	(-0.832)	(-0.883)
Horizon	0.000	0.000	0.000*	0.000*	0.000	0.000
	(1.536)	(0.573)	(1.782)	(1.905)	(1.322)	(1.372)
Gen_Exp	-0.001***	-0.001**	-0.000	0.003	0.003	-0.001
	(-5.152)	(-2.181)	(-0.954)	(0.950)	(1.254)	(-0.107)
Firm_Exp	0.002***	0.002**	0.001*	0.001	-0.000	-0.000
	(6.805)	(2.111)	(1.821)	(0.746)	(-0.093)	(-0.221)
Port_Size	0.000	0.000	-0.001	-0.002*	-0.003**	-0.003**
	(0.978)	(0.393)	(-0.844)	(-1.698)	(-2.183)	(-2.203)
SIC2_Count	-0.004**	-0.004	0.003	0.002	0.002	0.002
	(-2.575)	(-0.931)	(0.593)	(0.599)	(0.388)	(0.399)
Broker	0.000	0.000	0.000	-0.000	-0.001	-0.001
	(1.458)	(0.605)	(0.830)	(-0.726)	(-1.092)	(-1.096)
Size	0.007***	0.007	0.000	-0.015	-0.063*	-0.060*
	(3.462)	(0.840)	(0.007)	(-1.646)	(-1.792)	(-1.693)
MTB	-0.006***	-0.006***	-0.006***	-0.004***	-0.003***	-0.003***
	(-20.262)	(-4.978)	(-4.780)	(-3.814)	(-2.746)	(-2.690)
ROA	-1.175***	-1.175**	-1.238***	-1.438***	-1.224***	-1.237***
	(-9.621)	(-2.559)	(-2.678)	(-3.677)	(-2.770)	(-2.800)
Leverage	0.298***	0.298***	0.294***	0.348***	0.507***	0.499***
	(23.698)	(4.445)	(4.012)	(4.772)	(4.348)	(4.292)
Loss	0.254***	0.254***	0.253***	0.179***	0.080***	0.078***
	(28.924)	(6.959)	(6.890)	(5.734)	(2.856)	(2.806)
Ret_Vol	4.617***	4.617***	4.510***	3.605***	2.420***	2.372***
	(74.323)	(11.303)	(11.043)	(9.573)	(7.358)	(7.264)
Analyst_Follow	-0.010***	-0.010***	-0.010***	-0.007***	-0.003***	-0.003***
	(-25.849)	(-6.797)	(-6.344)	(-6.254)	(-3.044)	(-3.065)
HHI	-0.201***	-0.201***	-0.116*	-0.074	0.101	0.097
	(-14.002)	(-3.715)	(-1.952)	(-0.805)	(0.702)	(0.672)
DELIST	-0.024***	-0.024	-0.022	-0.010	-0.008	-0.005
	(-4.382)	(-0.977)	(-0.976)	(-0.695)	(-0.530)	(-0.336)
IPO	-0.012	-0.012	0.017	0.011	0.025	0.027
	(-1.352)	(-0.380)	(0.541)	(0.354)	(0.727)	(0.792)
Constant	-0.121***	-0.121	-0.098	-0.010	0.341	0.485
	(-5.679)	(-1.283)	(-1.032)	(-0.065)	(1.178)	(1.091)
Observations	65,212	65,212	65,212	65,212	65,212	65,212
Event FE	N	N	Y	Y	Y	Y
Analyst×Event FE	N	N	N	Y	Y	Y
Peer Firm×Event FE	N	N	N	N	Y	Y
Quarter-Cohort FE	N	N	N	N	N	Y
Cluster	N	Peer Firm	Peer Firm	Peer Firm	Peer Firm	Peer Firm
Adjusted R^2	0.186	0.186	0.197	0.312	0.448	0.449

This table examines the impact of cross-industry spinoffs on the forecast accuracy of the parent firm's close peers, relative to its distant peers. *FError* is the absolute difference between the most recent quarterly EPS forecast for the next fiscal quarter and the actual quarterly EPS, scaled by the stock price at the beginning of the quarter, times 100. Cross-industry spinoffs occur when the parent and spinoff firms have different 2-digit SIC codes afterwards. The table reports t-stats in the parenthesis. Standard errors are clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level respectively. Continuous variables are winsorized at the 1% and 99% levels. Variable definitions are reported in the appendix.

Table 10: Cross-Industry Spinoffs on the Forecast Dispersion of Peer Firms

Dependent	(1) *Disp*	(2) *Disp*	(3) *Disp*	(4) *Disp*	(5) *Disp*
Post	0.005	0.005	0.006	0.008	
	(0.739)	(0.626)	(0.791)	(0.856)	
Peer	0.071***	0.071**	0.054*		
	(5.855)	(2.502)	(1.915)		
Post×Peer	-0.051***	-0.051**	-0.053**	-0.052***	-0.053***
	(-3.036)	(-2.451)	(-2.531)	(-2.605)	(-2.621)
Size	0.012***	0.012*	0.005	-0.009	-0.012
	(4.413)	(1.823)	(0.743)	(-0.402)	(-0.482)
MTB	-0.003***	-0.003***	-0.002***	-0.001**	-0.001**
	(-7.110)	(-4.033)	(-3.735)	(-2.389)	(-2.329)
ROA	-0.506***	-0.506*	-0.556*	-0.498*	-0.504*
	(-2.881)	(-1.738)	(-1.913)	(-1.934)	(-1.961)
Leverage	0.231***	0.231***	0.244***	0.176**	0.166**
	(13.755)	(4.731)	(4.945)	(2.171)	(2.047)
Loss	0.136***	0.136***	0.133***	0.048***	0.047***
	(11.498)	(5.227)	(5.274)	(2.687)	(2.615)
Ret_Vol	2.334***	2.334***	2.262***	1.123***	1.095***
	(27.983)	(7.362)	(7.360)	(5.641)	(5.430)
Analyst_Follow	-0.005***	-0.005***	-0.005***	-0.000	-0.000
	(-8.052)	(-3.786)	(-3.542)	(-0.377)	(-0.375)
HHI	-0.000***	-0.000***	-0.000**	0.000	0.000
	(-8.315)	(-4.438)	(-2.419)	(0.565)	(0.443)
Delist	-0.009	-0.009	-0.014	-0.006	-0.005
	(-1.311)	(-0.483)	(-0.871)	(-0.659)	(-0.476)
IPO	-0.005	-0.005	0.020	-0.002	-0.001
	(-0.408)	(-0.209)	(0.892)	(-0.141)	(-0.089)
Constant	-0.188***	-0.188**	-0.143**	0.044	0.077
	(-7.325)	(-2.544)	(-2.222)	(0.253)	(0.419)
Observations	8,589	8,589	8,589	8,589	8,589
Event FE	N	N	Y	Y	Y
Peer Firm×Event FE	N	N	N	Y	Y
Quarter-Cohort FE	N	N	N	N	Y
Cluster	N	Peer Firm	Peer Firm	Peer Firm	Peer Firm
Adjusted R^2	0.197	0.197	0.222	0.536	0.538

This table examines the impact of cross-industry spinoffs on the forecast dispersion of the parent firm's close peers, relative to its distant peers. *Disp* is the standard deviation of the most recent quarterly EPS forecast, scaled by the stock price at the beginning of the quarter, times 100. Cross-industry spinoffs occur when the parent and spinoff firms have different 2-digit SIC codes afterwards. The table reports t-stats in the parenthesis. Standard errors are clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level respectively. Continuous variables are winsorized at the 1% and 99% levels. Variable definitions are reported in the appendix.

Table 11: Same-Industry Spinoffs on the Forecast Accuracy of Peer Firms

Dependent	(1) *FError*	(2) *FError*	(3) *FError*	(4) *FError*	(5) *FError*	(6) *FError*
Post	0.019***	0.019*	0.024**	0.036***	0.011	
	(3.862)	(1.822)	(2.220)	(3.264)	(0.644)	
Peer	0.020***	0.020	-0.004			
	(2.868)	(1.084)	(-0.157)			
Post×Peer	0.063***	0.063***	0.074***	0.090***	0.091***	0.090***
	(6.758)	(3.073)	(3.640)	(4.534)	(4.466)	(4.447)
Horizon	0.000	0.000	0.001***	0.000***	0.000***	0.000***
	(0.223)	(0.094)	(3.924)	(4.489)	(3.719)	(3.658)
Gen_Exp	-0.001***	-0.001***	-0.001*	-0.000	0.003	-0.005
	(-10.695)	(-3.975)	(-1.921)	(-0.193)	(1.309)	(-1.324)
Firm_Exp	0.000**	0.000	0.000	-0.000	0.000	0.000
	(2.140)	(0.747)	(0.153)	(-0.048)	(0.978)	(0.714)
Port_Size	0.001***	0.001	-0.003**	-0.001	-0.000	-0.000
	(3.867)	(1.091)	(-2.558)	(-1.070)	(-0.317)	(-0.150)
SIC2_Count	0.004***	0.004	0.009*	0.005***	0.008**	0.008**
	(3.365)	(0.978)	(1.863)	(2.852)	(2.447)	(2.412)
Broker	-0.000***	-0.000**	0.000	0.000	-0.000	-0.000
	(-6.361)	(-2.057)	(0.882)	(0.821)	(-0.838)	(-0.375)
Size	-0.014***	-0.014	-0.007	-0.114***	-0.116***	-0.114***
	(-7.367)	(-1.298)	(-0.635)	(-3.120)	(-3.041)	(-2.975)
MTB	-0.008***	-0.008***	-0.006***	-0.002	-0.002	-0.002
	(-29.739)	(-4.184)	(-3.693)	(-1.483)	(-1.406)	(-1.323)
ROA	-1.626***	-1.626***	-1.723***	-1.838***	-1.843***	-1.809***
	(-24.621)	(-3.303)	(-3.714)	(-5.419)	(-5.376)	(-5.298)
Leverage	0.498***	0.498***	0.449***	0.960***	0.951***	0.952***
	(45.553)	(5.979)	(5.266)	(7.243)	(7.048)	(7.065)
Loss	0.180***	0.180***	0.164***	0.039*	0.038	0.036
	(27.058)	(4.187)	(4.086)	(1.687)	(1.605)	(1.514)
Ret_Vol	4.428***	4.428***	4.128***	2.729***	2.742***	2.704***
	(86.223)	(11.804)	(11.767)	(8.193)	(8.041)	(7.995)
Analyst_Follow	-0.008***	-0.008***	-0.017***	-0.008***	-0.009***	-0.008***
	(-25.722)	(-4.664)	(-7.302)	(-5.066)	(-4.904)	(-4.881)
HHI	-0.301***	-0.301***	-0.116**	-0.042	-0.053	-0.067
	(-20.487)	(-4.534)	(-1.989)	(-0.442)	(-0.540)	(-0.684)
Delist	-0.026***	-0.026	-0.018	-0.014	-0.014	-0.012
	(-5.056)	(-1.281)	(-0.945)	(-0.894)	(-0.912)	(-0.781)
IPO	-0.052***	-0.052	-0.043	-0.044*	-0.042	-0.045*
	(-8.329)	(-1.586)	(-1.373)	(-1.670)	(-1.592)	(-1.689)
Constant	-0.008	-0.008	0.029	0.629**	0.555*	0.858**
	(-0.411)	(-0.076)	(0.285)	(2.031)	(1.803)	(2.397)
Observations	118,171	118,171	118,171	118,171	118,171	118,171
Event FE	N	N	Y	Y	Y	Y
Analyst×Event FE	N	N	N	N	Y	Y
Peer Firm×Event FE	N	N	N	Y	Y	Y
Quarter-Cohort FE	N	N	N	N	N	Y
Cluster	N	Peer Firm	Peer Firm	Peer Firm	Peer Firm	Peer Firm
Adjusted R^2	0.227	0.227	0.248	0.526	0.518	0.519

This table examines the impact of same-industry spinoffs on the forecast accuracy of the parent firm's close peers, relative to its distant peers. *FError* is the absolute difference between the most recent quarterly EPS forecast for the next fiscal quarter and the actual quarterly EPS, scaled by the stock price at the beginning of the quarter, times 100. Same-industry spinoffs occur when the parent and spinoff firms have the same 2-digit SIC codes afterwards. The table reports t-stats in the parenthesis. Standard errors are clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level respectively. Continuous variables are winsorized at the 1% and 99% levels. Variable definitions are reported in the appendix.

Table 12: Same-Industry Spinoffs on the Forecast Dispersion of Peer Firms

Dependent	(1) *Disp*	(2) *Disp*	(3) *Disp*	(4) *Disp*	(5) *Disp*
Post	0.004	0.004	0.007	0.012*	
	(0.619)	(0.550)	(0.969)	(1.876)	
Peer	0.027***	0.027**	0.015		
	(2.907)	(2.022)	(0.845)		
Post×Peer	0.038***	0.038***	0.045***	0.058***	0.060***
	(3.115)	(2.709)	(3.136)	(4.018)	(4.125)
Size	-0.003	-0.003	0.001	-0.047**	-0.054**
	(-1.153)	(-0.426)	(0.128)	(-1.965)	(-2.210)
MTB	-0.002***	-0.002**	-0.001	-0.000	-0.000
	(-7.699)	(-2.467)	(-1.472)	(-0.201)	(-0.186)
ROA	-1.077***	-1.077***	-1.055***	-1.476***	-1.442***
	(-11.481)	(-2.844)	(-2.986)	(-5.317)	(-5.224)
Leverage	0.284***	0.284***	0.254***	0.513***	0.501***
	(20.148)	(5.650)	(5.053)	(6.311)	(6.255)
Loss	0.084***	0.084***	0.073**	-0.016	-0.019
	(9.460)	(2.660)	(2.515)	(-1.125)	(-1.296)
Ret_Vol	2.743***	2.743***	2.557***	1.692***	1.697***
	(39.602)	(9.778)	(9.727)	(7.489)	(7.522)
Analyst_Follow	-0.002***	-0.002	-0.006***	-0.002**	-0.002*
	(-3.397)	(-1.466)	(-4.913)	(-2.009)	(-1.925)
HHI	-0.000***	-0.000***	-0.000	-0.000	-0.000
	(-9.329)	(-3.674)	(-1.336)	(-0.506)	(-0.929)
Delist	-0.009	-0.009	-0.010	-0.004	-0.002
	(-1.329)	(-0.706)	(-0.855)	(-0.497)	(-0.287)
IPO	-0.045***	-0.045**	-0.033*	-0.040***	-0.039***
	(-5.587)	(-2.082)	(-1.684)	(-2.954)	(-2.903)
Constant	-0.152***	-0.152**	-0.117	0.181	0.258
	(-6.769)	(-2.049)	(-1.544)	(0.880)	(1.211)
Observations	15,189	15,189	15,189	15,189	15,189
Event FE	N	N	Y	Y	Y
Peer Firm×Event FE	N	N	N	Y	Y
Quarter-Cohort FE	N	N	N	N	Y
Cluster	N	Y	Y	Y	Y
Adjusted R^2	0.276	0.276	0.311	0.609	0.611

This table presents the impact of same-industry spinoffs on the forecast dispersion of the parent firm's close peers, relative to distant peers. *Disp* is the standard deviation of the most recent quarterly EPS forecast, scaled by the stock price at the beginning of the quarter, times 100. Same-industry spinoffs occur when the parent and spinoff firms have the same 2-digit SIC codes afterwards. The table reports t-stats in the parenthesis. Standard errors are clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level respectively. Continuous variables are winsorized at the 1% and 99% levels. Variable definitions are reported in the appendix.

Table 13: Cross-Industry Spinoffs – Complexity of Pre-Parent Firm

Panel A: Descriptives							
Number of Segments	2	3	4	5	6	7	
Number of Spinoffs	6	14	8	4	2	1	Total: 35

Panel B: Multivariate Results				
	(1)	(2)	(3)	(4)
Dependent	*FError*	*FError*	*Disp*	*Disp*
Subsample	# of Segments Below Median	# of Segments Above Median	# of Segments Below Median	# of Segments Above Median
Post×Peer	0.087	-0.059	0.024	-0.083**
	(1.555)	(-1.322)	(0.779)	(-2.497)
Observations	11,559	27,095	1,599	3,095
Adjusted R^2	0.465	0.476	0.671	0.576
Event FE	Y	Y	Y	Y
Analyst×Event FE	Y	Y	N	N
Firm×Event FE	Y	Y	Y	Y
Quarter-Cohort FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Cluster	Peer Firm	Peer Firm	Peer Firm	Peer Firm
F-Test	f-stat = 5.15, p-value = 0.024		f-stat = 9.83, p-value < 0.01	

This table examines whether the impact of cross-industry spinoffs on the forecast accuracy and forecast dispersion of the parent firm's peer firms is moderated by the number of business segments of the pre-parent firm. # of Segments Below (Above) Median indicates whether the number of business segments by the pre-parent firm is below (above) the median. Panel A provides descriptive statistics on the number of cross-industry spinoffs in which the pre-parent firm has a certain number of business segments. Panel B presents the multivariate results. Columns 1 and 2 presents the forecast accuracy analysis. Columns 3 and 4 presents the forecast dispersion analysis. *FError* is the absolute difference between the most recent quarterly EPS forecast for the next fiscal quarter and the actual quarterly EPS, scaled by the stock price at the beginning of the quarter, times 100. *Disp* is the standard deviation of the most recent quarterly EPS forecast, scaled by the stock price at the beginning of the quarter, times 100. To calculate the f-stat, I create a binary variable, *Complex*, that equals 1 if the number of segments in the pre-parent firm is above the median number of segments, and 0 otherwise. I then test whether the sum of the coefficients of *Post×Complex* and *Post×Peer×Complex* is significantly different from zero. Cross-industry spinoffs occur when the parent and spinoff firms have different 2-digit SIC codes afterwards. The table reports t-stats in the parenthesis. Standard errors are clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level respectively. Continuous variables are winsorized at the 1% and 99% levels. Variable definitions are reported in the appendix.

Table 14: Same-Industry Spinoffs – Change in Industry Concentration

Dependent	(1) *HHI*	(2) *HHI*	(3) *HHI*	(4) *HHI*	(5) *HHI*
Post	0.019***	0.019***	0.011***	0.009***	
	(6.062)	(6.491)	(4.324)	(4.518)	
Peer	-0.049***	-0.049***	-0.057***		
	(-10.037)	(-10.448)	(-8.845)		
Post×Peer	-0.030***	-0.030***	-0.019***	-0.007***	-0.006***
	(-4.880)	(-8.360)	(-5.980)	(-3.177)	(-2.818)
Observations	12,737	12,737	12,737	12,737	12,737
Controls	Y	Y	Y	Y	Y
Event FE	N	N	Y	Y	Y
Peer Firm×Event FE	N	N	N	Y	Y
Year-Cohort FE	N	N	N	N	Y
Cluster	N	Peer Firm	Peer Firm	Peer Firm	Peer Firm
Adjusted R^2	0.203	0.203	0.368	0.947	0.948

This table examines the impact of same-industry spinoffs on the industry concentration of the parent firm's close peers, relative to its distant peers. *HHI* is the Herfindahl-Hirschman Index, measured as the sum of squared market share of a firm's annual net sales within the peer firm's 4-digit SIC code level. The regression controls for changes in industry concentration due to delisting and IPOs. Same-industry spinoffs occur when the parent and spinoff firms have the same 2-digit SIC codes afterwards. The table reports t-stats in the parenthesis. Standard errors are clustered by peer firm. *, **, *** indicate significance at the 10%, 5% and 1% level respectively. Continuous variables are winsorized at the 1% and 99% levels. Variable definitions are reported in the appendix

Table 15: Same Industry Spinoffs - Industry Concentration

	(1)	(2)	(3)	(4)
Dependent	*FError*	*FError*	*Disp*	*Disp*
Subsample	*HHI* Increase	*HHI* Decrease	*HHI* Increase	*HHI* Decrease
Post×Peer	0.031	0.109***	-0.015	0.100***
	(1.239)	(4.068)	(-0.810)	(5.354)
Observations	54,713	62,976	7,229	7,886
Controls	Y	Y	Y	Y
Event FE	Y	Y	Y	Y
Analyst×Event FE	Y	Y	N	N
Peer Firm×Event	Y	Y	Y	Y
Quarter-Cohort FE	Y	Y	Y	Y
Cluster	Peer Firm	Peer Firm	Peer Firm	Peer Firm
Adjusted R^2	0.479	0.531	0.553	0.650
F-Test	f-stat = 11.20, p-value <0.01		f-stat = 17.91, p-value < 0.01	

This table examines whether the decrease in forecast accuracy and increase in forecast dispersion after a same-industry spinoff is moderated by changes in the peer firm's industry concentration. *HHI* the sum of squared market share of a peer firm's annual net sales within the peer firm's four-digit SIC code. Industry Concentration Increase (Decrease) indicates that the average *HHI* of the peer firm in the post-spinoff period is greater (less than) the average *HHI* of the peer firm in the pre-spinoff period. Columns 1 and 2 presents the forecast accuracy analysis. Columns 3 and 4 presents the forecast dispersion analysis. *FError* is the absolute difference between the most recent quarterly EPS forecast for the next fiscal quarter and the actual quarterly EPS, scaled by the stock price at the beginning of the quarter, times 100. *Disp* is the standard deviation of the most recent quarterly EPS forecast, scaled by the stock price at the beginning of the quarter, times 100. To calculate the f-stat, I create a binary variable, *HHI_Inc*, that equals 1 if the HHI of the peer firm increased in the post-spinoff period, relative to the pre-spinoff period, and 0 otherwise. I then test whether the sum of the coefficients of *Post×HHI_Inc* and *Post×Peer×HHI_Inc* is significantly different from zero. Same-industry spinoffs occur when the parent and spinoff firms have the same 2-digit SIC codes afterwards. The table reports t-stats in the parenthesis. Standard errors are clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level respectively. Continuous variables are winsorized at the 1% and 99% levels. Variable definitions are reported in the appendix.

Table 16: Same-Industry Spinoffs – Change in Volatility of Peer Firm Fundamentals

	(1)	(2)	(3)
Dependent	*Cash_Vol*	*OpInc_Vol*	*IncBefExtra_Vol*
Post×Peer	2.887	21.632***	15.997**
	(0.534)	(3.330)	(2.380)
Observations	30,381	30,381	30,381
Controls	Y	Y	Y
Event FE	Y	Y	Y
Peer Firm×Event FE	Y	Y	Y
Quarter-Cohort FE	Y	Y	Y
Cluster	Peer Firm	Peer Firm	Peer Firm
Adjusted R^2	0.848	0.599	0.466

This table examines the impact of same-industry spinoffs on the cash flow and income volatility of the parent firm's close peers, relative to distant peers. *Cash_Vol* is the standard deviation of quarterly operating cash flow for the previous four quarters. *Income_Vol* is the standard deviation of quarterly operating income before depreciation for the previous four quarters. *IncBefExtra_Vol* is the standard deviation of quarterly income before extraordinary items for the previous four quarters. The regression controls for *Size*, *Leverage* and *MTB*. Same-industry spinoffs occur when the parent and spinoff firms have the same 2-digit SIC codes afterwards. The table reports t-stats in the parenthesis. Standard errors are clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level respectively. Continuous variables are winsorized at the 1% and 99% levels. Variable definitions are reported in the appendix.

Table 17: Same-Industry Spinoffs – Volatility in Peer Firm Fundamentals

Panel A: Change in Peer Firm's Operating Cash Flow Volatility

	(1)	(2)	(3)	(4)
Dependent	*FError*	*FError*	*Disp*	*Disp*
Subsample	*Cash_Vol* Increase	*Cash_Vol* Decrease	*Cash_Vol* Increase	*Cash_Vol* Decrease
Post×Peer	0.110***	0.040	0.061***	0.051**
	(4.695)	(1.097)	(3.639)	(1.979)
Observations	71,546	46,611	9289	5900
Controls	Y	Y	Y	Y
Event FE	Y	Y	Y	Y
Analyst×Event FE	Y	Y	N	N
Peer Firm×Event FE	Y	Y	Y	Y
Quarter-Cohort FE	Y	Y	Y	Y
Cluster	Firm	Firm	Firm	Firm
Adjusted R^2	0.486	0.553	0.581	0.650
F-Test	f-stat = 4.09, value = 0.0434		f-stat = 0.90, p-value = 0.3443	

Panel B: Change in Peer Firm's Operating Income Volatility

	(1)	(2)	(3)	(4)
Dependent	*FError*	*FError*	*Disp*	*Disp*
Subsample	*Income_Vol* Increase	*Income_Vol* Decrease	*Income_Vol* Increase	*Income_Vol* Decrease
Post×Peer	0.104***	0.045	0.082***	-0.001
	(4.466)	(1.192)	(4.836)	(-0.069)
Observations	73,322	44,835	9,290	5,899
Controls	Y	Y	Y	Y
Event FE	Y	Y	Y	Y
Analyst×Event FE	Y	Y	N	N
Peer Firm×Event FE	Y	Y	Y	Y
Quarter-Cohort FE	Y	Y	Y	Y
Cluster	Firm	Firm	Firm	Firm
Adjusted R^2	0.523	0.493	0.639	0.539
F-Test	f-stat = 2.38, p-value = 0.1235		f-stat = 10.90, p-value = 0.01	

Panel C: Change in Peer Firm's Income Before Extraordinary Items				
	(1)	(2)	(3)	(4)
Dependent	*FError*	*FError*	*Disp*	*Disp*
Subsample	*IncBefExtra_Vol* Increase	*IncBefExtra_Vol* Decrease	*IncBefExtra_Vol* Increase	*IncBefExtra_Vol* Decrease
Post×Peer	0.084***	0.080**	0.069***	0.030
	(3.531)	(2.179)	(3.809)	(1.404)
Observations	78,173	39,984	9,946	5,243
Controls	Y	Y	Y	Y
Event FE	Y	Y	Y	Y
Analyst×Event FE	Y	Y	N	N
Peer Firm×Event FE	Y	Y	Y	Y
Quarter-Cohort FE	Y	Y	Y	Y
Cluster	Peer Firm	Peer Firm	Peer Firm	Peer Firm
Adjusted R^2	0.507	0.534	0.609	0.625
F-Test	f-stat = 3.33, p-value 0.068		f-stat = 6.66, p-value = 0.01	

This table examines whether the decrease in forecast accuracy and increase in forecast dispersion after a same-industry spinoff are moderated by changes in cash flow and income volatility of peer firms. *FError* is the absolute difference between the most recent quarterly EPS forecast for the next fiscal quarter and the actual quarterly EPS, scaled by the stock price at the beginning of the quarter, times 100. *Disp* is the standard deviation of the most recent quarterly EPS forecast, scaled by the stock price at the beginning of the quarter, times 100. Panel A examines changes in *Cash_Vol*, which is the standard deviation of the peer firm's operating cash flow for the previous four quarters. To calculate the f-stat, I create a binary variable, *CF_Vol_Inc*, that equals 1 if *Cash_Vol* of the peer firms increased in the post-spinoff period, and 0 otherwise. I then test whether the sum of coefficients of *Post×CF_Vol_Inc* and *Post×Peer× CF_Vol_Inc* is significantly different from zero. Panel B examines changes in *OpInc_Vol*, which is the standard deviation of the peer firm's operating income before depreciation for the previous four quarters. To calculate the f-stat, I create a binary variable *Income_Vol_Inc*, that equals 1 if *Income_Vol* of the peer firms increased in the post-spinoff period and 0 otherwise. I then test whether the sum of coefficients of *Post×Income_Vol_Inc* and *Post×Peer×Income_Vol_Inc* is significantly different from zero. Panel C examines changes in *IncBefExtra_Vol*, which is the standard deviation of the peer firm's income before extraordinary items for the previous four quarters. To calculate the f-stat, I create a binary variable *IncBefExtra_Vol_Inc*, that equals 1 if *IncBefExtra _Vol* of the peer firms increased in the post-spinoff period and 0 otherwise. I then test whether the sum of coefficients of *Post×IncBefExtra_Vol_Inc* and *Post×Peer×IncBefExtra_Vol_Inc* is significantly different from zero. Increase (Decrease) indicates whether the volatility measure increased (decreased) in the post-spinoff period, relative to the pre-spinoff period. Same-industry spinoffs are spinoffs in which the parent and spinoff firms have the same 2-digit SIC codes afterwards. The table reports t-stats in the parenthesis. Standard errors are clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level respectively. Continuous variables are winsorized at the 1% and 99% levels. Variable definitions are reported in the appendix

Table 18: Same-Industry Spinoffs – Incremental Segment Disclosures

	Post-Parent Firm Provides Incremental Segment Disclosures				Spinoff Firm Provides Incremental Segment Disclosures			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent	*FError*	*FError*	*Disp*	*Disp*	*FError*	*FError*	*Disp*	*Disp*
Subsample	Same Segments	Different Segments	Same Segments	Different Segments	Same Segments	Different Segments	Same Segments	Different Segments
Post×Peer	0.094***	0.051	0.069***	-0.002	0.094***	-0.007	0.057***	0.013
	(3.946)	(1.553)	(4.002)	(-0.086)	(4.023)	(-0.192)	(3.372)	(0.501)
Observations	88,024	30,147	11,285	3,904	82,553	35,618	10,224	4,965
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Event FE	Y	Y	Y	Y	Y	Y	Y	Y
Analyst×Event FE	Y	Y	N	N	Y	Y	N	N
Peer Firm×Event FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter-Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Peer Firm	Peer Firm	Peer Firm	Peer Firm	Peer Firm	Peer Firm	Peer Firm	Peer Firm
Adjusted R^2	0.514	0.545	0.607	0.649	0.527	0.617	0.640	0.455
F-Test	f-stat = 2.16 p-value = 0.1422		f-stat = 3.22 p-value = 0.073		f-stat = 11.70 p-value < 0.01		f-stat = 5.84 p-value = 0.0160	

This table examines if the decrease in forecast accuracy and increase in forecast dispersion is moderated by incremental segment disclosures from either the post-parent or spinoff firms. Columns 1 to 4 examine incremental disclosures by the post-parent firm, relative to the pre-parent firm. Columns 5 to 8 examine incremental disclosures by the spinoff firm, relative to the pre-parent firm, of its own operations. *FError* is the absolute difference between the most recent quarterly EPS forecast for the next fiscal quarter and the actual quarterly EPS, scaled by the stock price at the beginning of the quarter, times 100. *Disp* is the standard deviation of the most recent quarterly EPS forecast, scaled by the stock price at the beginning of the quarter, times 100. Same (Different) Segments indicates that the post-parent or spinoff firm does not (does) provide incremental segment disclosures, relative to the pre-parent firm. To calculate the f-stat, I create a binary variable, *Par_Seg_Inc*, that equals 1 if the post-parent firm or the spinoff firm provides incremental segment disclosures and 0 otherwise. I then test whether the sum of coefficients of *Post×Par_Seg_Inc* and *Post×Peer× Par_Seg_Inc* is statistically different from zero. Same-industry spinoffs are spinoffs in which the parent and spinoff firms have the same 2-digit SIC codes afterwards. The table reports t-stats in the parenthesis. Standard errors are clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level respectively. Continuous variables are winsorized at the 1% and 99% levels. Variable definitions are reported in the appendix.

Table 19: Information Uncertainty of Peer Firms

	Cross-Industry Spinoffs				Same-Industry Spinoffs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent	*FError*	*FError*	*Disp*	*Disp*	*FError*	*FError*	*Disp*	*Disp*
Subsample	Bid-Ask Below Median	Bid-Ask Above Median	Bid-Ask Below Median	Bid-Ask Above Median	Bid-Ask Below Median	Bid-Ask Above Median	Bid-Ask Below Median	Bid-Ask Above Median
Post×Peer	-0.011	-0.069	-0.021	-0.084**	0.021	0.169***	0.011	0.080***
	(-0.333)	(-0.989)	(-1.452)	(-2.429)	(1.399)	(3.591)	(0.979)	(3.680)
Observations	46,934	18,278	4,286	4,303	86,549	31,622	7,589	7,600
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Event FE	Y	Y	Y	Y	Y	Y	Y	Y
Analyst×Event FE	Y	Y	N	N	Y	Y	N	N
Peer Firm×Event FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter-Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Peer Firm	Peer Firm	Peer Firm	Peer Firm	Peer Firm	Peer Firm	Peer Firm	Peer Firm
Adjusted R^2	0.326	0.429	0.307	0.569	0.382	0.477	0.383	0.607
F-Test	f-stat = 0.60		f-stat = 3.91		f-stat = 25.99		f-stat = 18.95	
	p-value = 0.4400		p-value = 0.0486		p-value < 0.01		p-value < 0.01	

This table examines if the main results are moderated by the level of information uncertainty of peer firms in the pre-spinoff period. Columns 1 to 4 present the cross-industry spinoff sample while Columns 5 to 8 present the same-industry sample. *Bid_Ask* is the average daily bid-ask spread for the peer firm for 180 days ending the quarter-end before the 10-12B filing date. Below Median (Above Median) indicates that the bid-ask spread in the pre-spinoff is below (above) the median. *FError* is the absolute difference between the most recent quarterly EPS forecast for the next fiscal quarter and the actual quarterly EPS, scaled by the stock price at the beginning of the quarter, times 100. *Disp* is the standard deviation of the most recent quarterly EPS forecast, scaled by the stock price at the beginning of the quarter, times 100. To calculate the f-stat, I create a binary variable, *Uncertain*, that equals 1 if the *Bid_Ask* for a peer firm is greater than the median, and 0 otherwise. I then test whether the sum of the coefficients of *Post×Uncertain* and *Post×Peer×Uncertain* is statistically different from zero.Same-industry (cross-industry) spinoffs are spinoffs in which the parent and spinoff firms have the same (different 2-digit SIC codes in the post-spinoff period. The table reports t-stats in the parenthesis. Standard errors are clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level respectively. Continuous variables are winsorized at the 1% and 99% levels. Variable definitions are reported in the appendix.

Table 20: Parallel Trends Assumption

	(1)	(2)	(3)	(4)
Dependent	*FError*	*FError*	*Disp*	*Disp*
Subsample	Cross-Industry	Same-Industry	Cross-Industry	Same-Industry
Period1×Peer	0.069	0.021	0.073	0.029
	(1.473)	(0.668)	(1.567)	(0.973)
Period2×Peer	-0.004	0.003	0.005	-0.007
	(-0.101)	(0.092)	(0.169)	(-0.280)
Period3×Peer	0.046	-0.009	0.002	0.007
	(1.147)	(-0.333)	(0.056)	(0.271)
Period4×Peer	-0.000	-0.004	0.042	0.031
	(-0.009)	(-0.141)	(0.883)	(1.316)
Period5×Peer	-0.006	-0.010	0.009	0.024
	(-0.125)	(-0.401)	(0.314)	(1.217)
Period7×Peer	0.007	0.025	-0.031	0.038
	(0.170)	(0.820)	(-1.050)	(1.560)
Period8×Peer	0.009	0.077*	-0.017	0.076**
	(0.213)	(1.831)	(-0.620)	(2.424)
Period9×Peer	-0.002	0.088**	-0.053	0.056**
	(-0.038)	(2.422)	(-1.499)	(2.035)
Period10×Peer	-0.037	0.087**	-0.047	0.061*
	(-0.714)	(2.037)	(-1.448)	(1.917)
Period11×Peer	-0.042	0.161***	-0.021	0.083**
	(-0.881)	(3.858)	(-0.573)	(2.578)
Period12×Peer	0.007	0.109***	-0.041*	0.146***
	(0.114)	(2.728)	(-1.702)	(3.934)
Observations	65,212	118,171	8,388	14,900
Controls	Y	Y	Y	Y
Event FE	Y	Y	Y	Y
Analyst×Event FE	Y	Y	N	N
Peer Firm×Event FE	Y	Y	Y	Y
Quarter-Cohort FE	Y	Y	Y	Y
Cluster	Peer Firm	Peer Firm	Peer Firm	Peer Firm
Adjusted R^2	0.449	0.519	0.500	0.597

This table examines the parallel trends assumption. *FError* is the absolute difference between the most recent quarterly EPS forecast for the next fiscal quarter and the actual quarterly EPS, scaled by the stock price at the beginning of the quarter, times 100. *Disp* is the standard deviation of the most recent quarterly EPS forecast, scaled by the stock price at the beginning of the quarter, times 100. *Period* is a set of dummy variables that equals 1 for a given quarter in the pre-spinoff and post-spinoff periods. Same-industry spinoffs are spinoffs in which the parent and spinoff firms have the same 2-digit SIC codes afterwards. Same-industry (cross-industry) spinoffs are spinoffs in which the parent and spinoff firms have the same (different) 2-digit SIC codes afterwards. The table reports t-stats in the parenthesis. Standard errors are clustered by peer firm. *, **, *** indicate significance at the 10%, 5% and 1% level respectively. Continuous variables are winsorized at the 1% and 99% levels. Variable definitions are reported in the appendix.

Table 21: Descriptives – Entropy Balancing

Panel A: Cross-Industry Spinoffs

	Before Reweighting						After Reweighting					
	Close Peers			Distant Peers			Close Peers			Distant Peers		
	Mean	Var	Skew	Mean	Var	Skew	Mean	Var	Skew	Mean	Var	Skew
Horizon	42.59	995.80	0.38	54.61	1085.00	-0.30	42.59	995.80	0.38	42.59	995.80	0.38
Gen_Exp	37.56	478.10	0.53	40.60	464.60	0.56	37.56	478.10	0.53	37.56	478.10	0.53
Firm_Exp	17.02	169.60	1.29	15.73	121.30	0.99	17.02	169.60	1.29	17.02	169.50	1.29
Port_Size	14.81	45.65	0.56	12.62	33.65	0.86	14.81	45.65	0.56	14.81	45.65	0.56
SIC2_Count	3.40	3.39	0.94	3.74	3.92	0.66	3.40	3.39	0.94	3.40	3.39	0.94
Broker_Size	50.63	957.60	-0.03	46.86	936.40	0.22	50.63	957.60	-0.03	50.63	957.60	-0.03
Size	9.18	3.20	-0.13	8.58	2.92	0.04	9.18	3.20	-0.13	9.18	3.20	-0.13
MTB	3.24	26.83	5.35	4.19	63.31	4.05	3.24	26.83	5.35	3.24	26.83	5.35
ROA	0.01	0.00	-2.22	0.01	0.00	-2.73	0.01	0.00	-2.22	0.01	0.00	-2.22
Leverage	0.55	0.03	-0.10	0.57	0.05	0.15	0.55	0.03	-0.10	0.55	0.03	-0.10
Loss	0.12	0.11	2.35	0.16	0.14	1.84	0.12	0.11	2.35	0.12	0.11	2.35
Ret_Vol	0.09	0.00	1.30	0.09	0.00	1.43	0.09	0.00	1.30	0.09	0.00	1.30
Analyst_Follow	13.92	49.19	0.51	12.65	58.99	0.78	13.92	49.19	0.51	13.92	49.19	0.51
Delist	0.75	0.19	-1.17	0.62	0.24	-0.48	0.75	0.19	-1.17	0.75	0.19	-1.17
IPO	0.13	0.11	2.24	0.07	0.06	3.48	0.13	0.11	2.24	0.13	0.11	2.24

Panel B: Same-Industry Spinoffs

	Before Reweighting						After Reweighting					
	Close Peers			Distant Peers			Close Peers			Distant Peers		
	Mean	Var	Skew	Mean	Var	Skew	Mean	Var	Skew	Mean	Var	Skew
Horizon	43.87	969.50	0.26	49.42	1039.00	-0.03	43.87	969.50	0.26	43.87	969.50	0.26
Gen_Exp	35.42	440.80	0.59	40.34	551.60	0.58	35.42	440.80	0.59	35.42	440.90	0.59
Firm_Exp	14.28	128.60	1.39	16.29	145.90	1.10	14.28	128.60	1.39	14.28	128.60	1.39
Port_Size	15.13	45.07	0.53	14.06	39.65	0.74	15.13	45.07	0.53	15.13	45.07	0.53
SIC2_Count	2.25	2.51	1.72	3.26	3.91	0.85	2.25	2.51	1.72	2.25	2.51	1.72
Broker_Size	45.59	974.90	0.26	48.65	963.90	0.09	45.59	974.90	0.26	45.59	975.00	0.26
Size	8.19	3.37	-0.13	8.59	2.54	-0.31	8.19	3.37	-0.13	8.19	3.37	-0.13
MTB	4.59	62.13	3.62	4.54	73.06	4.01	4.59	62.13	3.62	4.59	62.14	3.63
ROA	-0.01	0.00	-1.76	0.01	0.00	-3.20	-0.01	0.00	-1.76	-0.01	0.00	-1.76
Leverage	0.52	0.05	0.34	0.57	0.04	0.04	0.52	0.05	0.34	0.52	0.05	0.34
Loss	0.38	0.24	0.49	0.20	0.16	1.51	0.38	0.24	0.49	0.38	0.24	0.49
Ret_Vol	0.11	0.00	1.08	0.09	0.00	1.55	0.11	0.00	1.08	0.11	0.00	1.08
Analyst_Follow	15.05	76.85	0.40	12.38	53.36	0.91	15.05	76.85	0.40	15.05	76.85	0.40
Delist	0.90	0.09	-2.58	0.60	0.24	-0.43	0.90	0.09	-2.58	0.90	0.09	-2.58
IPO	0.40	0.24	0.40	0.09	0.08	2.85	0.40	0.24	0.40	0.40	0.24	0.40

This table presents the mean, variance and skewness of the covariates for close and distant peers, before and after entropy balancing, in the forecast accuracy analysis. Panel A presents results for cross-industry spinoffs, while Panel B presents results for same-industry spinoffs. Variable definitions are reported in the appendix. Similar results for the forecast dispersion analysis are untabulated.

Table 22: Entropy Balancing

	(1)	(2)	(3)	(4)
Dependent	*FError*	*FError*	*Disp*	*Disp*
Subsample	Cross-Industry	Same-Industry	Cross-Industry	Same-Industry
Post×Peer	-0.024	0.033	-0.062***	0.015
	(-0.796)	(1.540)	(-3.016)	(0.875)
Observations	65,212	118,171	8,589	15,189
Controls	Y	Y	Y	Y
Event FE	Y	Y	Y	Y
Analyst×Event FE	Y	Y	N	N
Peer Firm×Event FE	Y	Y	Y	Y
Quarter-Cohort FE	Y	Y	Y	Y
Cluster	Peer Firm	Peer Firm	Peer Firm	Peer Firm
Adjusted R^2	0.454	0.507	0.582	0.619

This table reexamines the main analysis using entropy balancing. Covariates are balanced across the first, second and third moments. *FError* is the absolute difference between the most recent quarterly EPS forecast for the next fiscal quarter and the actual quarterly EPS, scaled by the stock price at the beginning of the quarter, times 100. *Disp* is the standard deviation of the most recent quarterly EPS forecast, scaled by the stock price at the beginning of the quarter, times 100. Same-industry spinoffs are spinoffs in which the parent and spinoff firms have the same 2-digit SIC codes afterwards. Same-industry (cross-industry) spinoffs are spinoffs in which the parent and spinoff firms have the same (different) 2-digit SIC codes afterwards. The table reports t-stats in the parenthesis. Standard errors are clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level respectively. Continuous variables are winsorized at the 1% and 99% levels. Variable definitions are reported in the appendix

Table 23: Alternative Definitions of Peer Firms Using SIC Codes

	Expand the Definition of Distant Peers				Expand the Definition of Close Peers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent	*FError*	*FError*	*Disp*	*Disp*	*FError*	*FError*	*Disp*	*Disp*
Subsample	Cross-Industry	Same-Industry	Cross-Industry	Same-Industry	Cross-Industry	Same-Industry	Cross-Industry	Same-Industry
Post×*Peer*	-0.030	0.096***	-0.048***	0.061***	-0.001	0.024*	-0.015	0.023***
	(-1.139)	(4.769)	(-2.642)	(4.302)	(-0.073)	(1.911)	(-1.284)	(2.627)
Observations	79,761	153,401	10,375	19,465	82,444	153,401	11,348	20,482
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Event FE	Y	Y	Y	Y	Y	Y	Y	Y
Analyst×Event FE	Y	Y	N	N	Y	Y	N	N
Peer Firm×Event FE	Y	Y	Y	Y	Y	Y	Y	Y
Quarter-Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y
Cluster	Peer Firm	Peer Firm	Peer Firm	Peer Firm	Peer Firm	Peer Firm	Peer Firm	Peer Firm
Adjusted R^2	0.454	0.512	0.544	0.605	0.458	0.511	0.554	0.602

This table examines the impact of same-industry and cross-industry spinoffs on the forecast accuracy and forecast dispersion of the parent firm's peer firms using alternative SIC definitions for close and distant peers. In the main analysis, peer firms with the same three-digit SIC code but different four-digit SIC code as the pre-parent firm were excluded. In Columns 1 to 4, the definition of distant peers includes these excluded peer firms such that distant peers comprise firms that share the same two-digit SIC code, but different four-digit SIC code. In Columns 5 to 8, the definition of close peers includes these excluded peer firms, such that close peers comprise firms that share at least the same three-digit SIC code. *FError* is the absolute difference between the most recent quarterly EPS forecast for the next fiscal quarter and the actual quarterly EPS, scaled by the stock price at the beginning of the quarter, times 100. *Disp* is the standard deviation of the most recent quarterly EPS forecast, scaled by the stock price at the beginning of the quarter, times 100. Same-industry (cross-industry) spinoffs are spinoffs in which the parent and spinoff firms have the same (different) 2-digit SIC codes afterwards. The table reports t-stats in the parenthesis. Standard errors are clustered by firm. *, **, *** indicate significance at the 10%, 5% and 1% level respectively. Continuous variables are winsorized at the 1% and 99% levels. Variable definitions are reported in the appendix.

Table 24: Defining Close and Peer Firms Using NAICS Codes

	(1)	(2)	(3)	(4)
Dependent	*FError*	*FError*	*Disp*	*Disp*
Subsample	Cross-Industry	Same-Industry	Cross-Industry	Same-Industry
Post×Peer	0.001	0.046***	-0.015	0.022**
	(0.044)	(3.066)	(-1.344)	(2.167)
Observations	58,862	122,639	7,992	16,799
Controls	Y	Y	Y	Y
Event FE	Y	Y	Y	Y
Analyst×Event FE	Y	Y	N	N
Peer Firm×Event FE	Y	Y	Y	Y
Quarter-Cohort FE	Y	Y	Y	Y
Cluster	Peer Firm	Peer Firm	Peer Firm	Peer Firm
Adjusted R^2	0.464	0.457	0.559	0.555

This table redefines the parent firm's close and distant peers using North American Industry Classification System (NAICS) codes. Close peers share the same five-digit NAICS code as the pre-parent firm in the year before the initial filing date of the Form 10-12B. Distant peers share the same three-digit NAICS code but different four-digit NAICS code as the pre-parent firm in the year before the initial filing date of the Form 10-12B. The regression includes the same control variables, fixed effects and clustered standard errors as Equations (1) and (2). *FError* is the absolute difference between the most recent quarterly EPS forecast for the next fiscal quarter and the actual quarterly EPS, scaled by the stock price at the beginning of the quarter, times 100. *Disp* is the standard deviation of the most recent quarterly EPS forecast, scaled by the stock price at the beginning of the quarter, times 100. Same-industry (cross-industry) spinoffs occur when the parent and spinoff firms have the same (different) 2-digit SIC codes afterwards. The table reports t-stats in the parenthesis. Standard errors are clustered by peer firm. *, **, *** indicate significance at the 10%, 5% and 1% level respectively. Continuous variables are winsorized at the 1% and 99% levels. Variable definitions are reported in the appendix.