Target Selection and Shareholder Value Implications in Operating Synergy-Driven Mergers

by

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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

This study examines whether resource similarity in product and geographic market positions, as well as resource quality similarity, affects the likelihood of related mergers aimed at operating synergies. I classify five value-creation sources of operating synergies: cost efficiency, market position, product portfolio, geographic expansion, and innovation resources. Product and geographic market resources are critical to achieving these value-creation goals, while variation in resource quality among potential targets possessing the necessary resources indicates different gains acquirers can retain from synergy distribution.

I estimate conditional logit models for target selection analyses and ordinary least squares regressions for shareholder wealth effect analyses. The results show that all three dimensions of similarity increase merger likelihood, although their effects vary across value-creation contexts. I find evidence consistent with acquirers' expectations of net gains from synergy distribution when selecting targets exhibiting product similarity and resource quality similarity, as reflected by closer Tobin's Qs.

Product similarity consistently increases merger likelihood, yet its effect on acquirer shareholder wealth depends on the specific value-creation motive, reflecting its varying relevance across goals. Resource quality similarity primarily matters in product-enrichment-driven mergers. Its varying effect across value-creation contexts likely depends on the substitutability of the resources sought by acquirers. Geographic proximity increases the likelihood of operating synergy-driven mergers other than innovation-driven ones, but does not affect shareholder wealth outcomes. Its effect on merger likelihood appears driven by reduced information asymmetry between nearby firms, which may not enhance shareholder wealth creation.

This study adds new evidence on the determinants of target selection and merger performance across distinct value-creation contexts of operating synergies. This study also advances the literature on resource quality similarity by enriching evidence on its positive effect on merger likelihood and providing the first empirical evidence that the substitutability of the resources sought by acquirers moderates the strength of the positive relationship. The findings also indicate that requiring disclosure of primary reasons for mergers upon announcements may enhance acquirers' decision-making and external monitoring in operating synergy-driven mergers.

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Dedication

I dedicate this dissertation to my family, my friends, and the friends of my family.

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CHAPTER 1 INTRODUCTION

1.1 Introduction

Between 2004 and 2022, approximately nine percent of U.S. public firms were acquired by other U.S. public firms, with annual deal values totaling $561 billion. However, acquiring firms often fail to realize expected synergies and underperform their non-acquiring peers in subsequent years (e.g., Renneboog and Vansteenkiste 2019). Notably, about 80 percent of public mergers occur between firms in related industries, hereafter referred to as related mergers.[1] The setting of related mergers is economically important given its monetary and strategic significance in the industry economy.[2] It also warrants separate examination to advance the mergers and acquisitions (M&As) literature, as King, Dalton, Daily, and Covin (2004) find that variation in post-merger performance arises primarily within, rather than between, the subgroups of related and unrelated mergers.[3]

Related mergers are primarily driven by operating synergies, which stem from enhanced cross-functional decision-making through the integration of merging firms' resources, leading to higher net operating cash flows compared to the sum of their stand-alone going concern values (e.g., Seth 1990a). While operating synergy-driven mergers offer the potential to generate substantial gains, they also pose high risks of post-merger integration failure, potentially resulting in greater losses (Rabier 2017). Therefore, articulating a clear merger rationale and selecting an appropriate target are critical to realizing anticipated synergies.[4]

Despite its importance, research on acquirers' decision-making before announcing a merger remains limited (Welch, Pavićević, Keil, and Laamanen 2020; King et al. 2004). Target

[1] I define firms in related industries as U.S. public firms operating in the same industry or in vertically related industries. Two industries are defined as vertically related if one industry purchases at least five percent of its inputs from the other or sells at least five percent of its outputs to the other, and vice versa (Haunschild 1994). The percentage of related mergers in a given study's sample may vary depending on sample selection criteria and the definition of relatedness (Fan and Lang 2000).

[2] Take two cases with contrasting performance outcomes for illustration. *Coca-Cola Company*'s acquisition of *Coca-Cola Enterprise North America* cost $12 billion, nearing ten percent of the acquirer's pre-merger market capitalization, and *AT&T*'s acquisition of *Time Warner* cost $85.4 billion, more than one-third of the acquirer's pre-merger market capitalization. Both deals aimed to improve cost efficiency by forming a vertically integrated company, and both had a significant impact on the relevant industries.

[3] Focusing exclusively on related mergers when examining determinants of target selection and merger performance is unlikely to introduce statistical bias from self-selection. The authors emphasize the need for subgroup-level analysis.

[4] See https://www.vlerick.com/en/insights/wrong-target-wrong-price-and-poor-integration-that-s-where-m-a-goes-wrong/, featuring a keynote speech for corroborating perspectives on the importance of clarifying value-creation motives and target selection in mergers and acquisitions (accessed on April 15, 2025).

selection in operating synergy-driven mergers involves three core, recursive decisions: (i) clarifying the value-creation motive; (ii) identifying candidates possessing the necessary resources to fulfill that motive; and (iii) selecting and negotiating with the target expected to yield the highest net present value of net gains from the merger (Dyer, Godfrey, Jensen, and Bryce 2024; Welch et al. 2020). Product similarity and geographic proximity are especially relevant in the first two stages when screening target candidates for strategic and operational fit. The similarity in resource quality, measured by closer Tobin's Qs, becomes critical in the final selection stage when multiple candidates possess the requisite resources. Gaining insight into these determinants and their implications for value creation is especially important for operating synergy-driven mergers and holds relevance for both scholars and practitioners. This study examines how interfirm similarities in product portfolios, geographic markets, and resource quality influence target selection and shareholder wealth outcomes when acquirers pursue mergers for operating synergies.

One major obstacle in advancing this understanding is the limited availability of structured data that delineates acquirers' merger motives and pre-announcement decisions. For material mergers, the Securities Exchange Act mandates acquirers to disclose information relevant to investor decision-making through Form 8-K filings. Accounting Standards Codification (ASC) 805 requires disclosure of the primary reasons for a merger in post-merger financial statements. Information that is required to be disclosed post-merger but available at the merger announcement should be disclosed upon announcement, especially if it can affect investors' decision-making. I hand-collected acquirer executives' statements of merger rationales from merger announcements. However, these semi-structured disclosures often necessitate subjective interpretation to identify a single, primary motive. Following Rabier (2017), I classify five value-creation motives related to operating synergies: improving cost efficiency, enhancing market position, product enrichment, geographic expansion, and acquiring innovation resources.[5] I then determine each merger's primary motive using a double-coder reconciliation process detailed in Appendix C.

I identify a sample of 459 related mergers announced between 2004 and 2021 for target selection analyses, each with an identifiable value-creation goal related to operating synergies. Among these, 452 mergers have complete data for analyzing the effects on shareholder wealth outcomes. To analyze acquirers' target selection, I estimate conditional logit models (CLM) with

[5] See Appendix C.3 for excerpts from five mergers categorized into the five value-creation motives, respectively.

group fixed effects using 459 matched groups of actual and control mergers. Each actual acquirer is matched with up to five control target firms to construct control mergers, with control targets matched using the nearest-neighbor propensity score matching without replacement. To examine shareholder wealth effects, I employ ordinary least squares (OLS) regression models with fixed effects for the acquirer industry and merger announcement year.

I find that product similarity increases the likelihood of operating synergy-driven mergers equally across all five value-creation contexts. The results indicate that geographic proximity increases the likelihood of operating synergy-driven mergers. The effect varies by value-creation motive: it is strongest in mergers aimed at geographic expansion and weakest in those motivated by product portfolio enrichment. Geographic proximity does not significantly influence the likelihood of mergers aimed at accessing innovation resources. From the synergy perspective, I expect product similarity and geographic proximity to jointly enhance synergy potential in mergers aimed at enhancing cost efficiency and market position, but not in other contexts. The results are consistent with this expectation. Overall, the findings are consistent with the interpretation that acquirers' value-creation goals drive the observed positive effects of product similarity and geographic proximity on merger likelihood.

Another possible mechanism underlying the positive effects of product similarity and geographic proximity is acquirers' preference for target firms with more accessible and easier-to-process information, given their bounded rationality, regardless of synergy potential. To explore this information asymmetry explanation, I test whether direct proxies for the accessibility of target firms' publicly available information and alternative private information channels moderate the originally observed positive effects. The findings suggest that reduced information asymmetry is unlikely to be the primary driver of mergers between firms with similar product portfolios; rather, the level of information asymmetry is already low before the merger announcement. Additionally, the results suggest that reduced information asymmetry contributes to the positive relationship between geographic proximity and merger likelihood, although it does not fully explain the association. Specifically, stock market information, closely connected boards, and geographic proximity appear to serve as substitute channels for reducing information asymmetry.

Tobin's Q similarity increases the likelihood of mergers motivated by operating synergies, particularly in product portfolio enrichment mergers. These findings motivate further examination

of an unexamined moderating factor: the substitutability of the resources sought by acquirers. Target resource substitutability reflects both the necessity and discretion acquirers exercise in assessing the quality of resources across multiple potential targets. The analyses show that the positive relationship between Q similarity and merger likelihood is more pronounced when substitutability is low. In such cases, potential target firms tend to exhibit heterogeneous resource quality, resulting in varying degrees of bargaining power and expected merger gains for the acquirer. As a result, switching among targets incurs costs, making rank-order matching based on resource quality a more critical consideration (Lentz and Mortensen 2010).

Consistent with synergy motive expectations, product similarity is significantly and positively associated with the net present value (NPV) of acquirers' expected gains from the merger (AGAIN). It is also negatively related to the relative bargaining power of the target. These effects are primarily observed in mergers aimed at improving cost efficiency and enhancing market position. Q similarity is likewise significantly and positively associated with both expected synergy and AGAIN, primarily in deals focused on enriching product portfolios. In contrast, geographic proximity shows no significant relationship with acquirer shareholder wealth outcomes. Lastly, the significant relationships with AGAIN and bargaining power are primarily driven by deals involving large acquirer gains or losses (i.e., $500 million or more).

1.2 Contributions to the Literature and Practice

The study contributes to four streams of literature. First, it advances the strategic management literature on mergers and acquisitions (M&As), particularly concerning the role of interfirm similarity in related mergers. Harrison, Hitt, Hoskisson, and Ireland (1991) argue that interfirm similarity affects merger performance differently in related versus unrelated mergers and call for research in specific value-creation contexts. King et al. (2004) similarly emphasize that post-merger performance variation arises from within-group differences and advocate focusing on why some mergers succeed while others fail in specific value-creation contexts. Both King et al. (2004) and Welch et al. (2020) highlight the importance of pre-merger antecedents, yet progress has been limited due to difficulties in identifying specific value-creation contexts. Recent advances include Phillips and Hoberg (2010), who measure product differentiation synergies; Bena and Li (2014), who examine innovation-driven mergers; and Rabier (2017), who compares financial versus operating synergy outcomes. This study contributes to this literature by providing evidence on

three important pre-announcement factors—product similarity, geographic proximity, and resource quality similarity—that influence merger decisions across five value-creation contexts related to operating synergies.

Second, this study extends the literature on resource quality similarity in merger partner selection. Prior studies document mixed evidence (e.g., Kaul and Wu 2016). Some studies suggest that mergers between firms with dissimilar governance strengths create value (Jovanovic and Rousseau 2002; Wang and Xie 2009), a pattern characterized as substitution-driven mergers. Rhodes-Kropf and Robinson (2008) propose that firms with similar resource quality, measured by Q similarity, are more likely to merge to access complementary resources. Complementarity and substitutability are typically inferred in hindsight based on empirical findings on Q similarity, except for Wang and Xie (2009), who provide evidence on substitution by directly examining interfirm similarity in entrenchment levels.

This study advances the literature by approaching complementarity versus substitutability through merging parties' disclosures that both expect operating synergy gains by resource integration, thereby deeming operating synergy-driven mergers as primarily complementarity-driven. Consistent with this framing, this study provides empirical evidence of a positive relationship between Q similarity and merger likelihood.

Furthermore, empirical support from Chen, Kim, and Rhee (2021) and Rhodes-Kropf and Robinson (2008) suggests that both macro- and micro-level factors reducing search costs facilitate the matching of firms with similar resource quality (i.e., closer Qs). Extending this line of inquiry, this study identifies related mergers pursuing operating synergies as a specific low search-cost setting, a necessary condition for the positive effect to emerge (Rhodes-Kropf and Robinson 2008). Within the low search-cost context, this study provides the first empirical evidence that the substitutability of the resources sought by acquirers moderates the positive relationship between Q similarity and merger likelihood.

Third, this study contributes to understanding how the information environment of public target firms affects merger outcomes. Prior studies suggest that the quality and quantity of target firms' publicly available information influence merger outcomes primarily in cross-industry mergers, with limited relevance to same-industry deals (Raman, Shivakumar, and Tamayo 2013; Martin and Shalev 2017; Perafán-Peña, Gill-de-Albornoz, and Giner 2022). This study provides

the first direct evidence that public information quality and quantity do not affect the likelihood of related mergers seeking operating synergies, whereas private information channels do. Moreover, this study finds substitution relationships among some private information channels.[6]

Fourth, this study contributes to the literature on negotiation power and synergy distribution in mergers. Prior studies link synergy distribution to agency problems (e.g., Moeller 2005), relative resource scarcity between merging firms (Rhodes-Kropf and Robinson 2008), asymmetric vertical dependence (Ahern 2012), and information asymmetry (e.g., Cai and Sevilir 2012; Chen et al. 2021). Fich, Nguyen, and Officer (2018) further emphasize the need to account for deals involving extreme gains or losses when assessing shareholder value effects. This study adds evidence to this literature. Aligning with Fich et al.'s (2018) recommendation, the findings that product and Q similarity are negatively associated with target bargaining power are primarily driven by deals involving acquirer gains or losses exceeding $500 million.[7] In subsamples with data on acquirer entrenchment, results show that product similarity reduces target bargaining power when acquirer entrenchment is low (i.e., shareholder rights are strong). Conversely, when acquirer entrenchment is high, both product and Q similarity correlate with more favorable negotiation outcomes for target firms.

These findings offer practical implications for strategic decision-makers and sophisticated investors evaluating merger potential. Acquirers should better identify potential sources of value-creation prior to bidding, assess whether alternative target candidates can provide the necessary resources, and evaluate expected gains considering each target candidate's relative bargaining power in synergy distribution. Investors with sufficient expertise can apply these insights to strengthen oversight of merger decisions. Additionally, requiring disclosure of primary merger rationales upon merger announcement may promote acquirers' self-discipline and assist investors in merger evaluation, potentially reducing the incidence of value-destructive deals.

[6] Some M&A studies provide insights into the information role of board interlocks, closely connected boards, common advisors, common auditors, common bank lenders, and common institutional shareholders (Haunschild and Beckman 1998; Cai and Sevilir 2012; Agrawal, Cooper, Lian, and Wang 2013; Ishii and Xuan 2014; Cai, Kim, Park, and White 2016; Dhaliwal, Lamoreaux, Litov, and Neyland 2016; Brooks, Chen, and Zeng 2018; Fee, Subramaniam, Wang, and Zhang 2019; Xia 2023)

[7] Hoberg and Phillips (2010) do not address how product similarity affects the relative bargaining power between merging firms. While Rhodes-Kropf and Robinson (2008) argue theoretically that Q similarity reflects a tradeoff between synergy potential and bargaining power, they do not empirically examine how Q similarity relates to acquirers' bargaining power.

1.3 Summary of the Thesis Structure

The rest of the thesis is organized as follows. Chapter 2 reviews the relevant literature. Chapter 3 presents theories of acquirer merger motives and develops the hypotheses. Chapter 4 describes the data, sample, measures, and primary research designs for hypothesis testing. Chapter 5 reports the empirical findings. Chapter 6 concludes the thesis.

CHAPTER 2 LITERATURE REVIEW

2.1 Determinants of Merger Probability

A transfer-of-control takeover begins when one firm seeks to acquire another or offers itself as a target. This section reviews prior studies on acquirer and target motives for initiating mergers, as well as empirical evidence on factors that, while not driving initiation, influence merger probability through their effects on merger completion and merger partner selection.

2.1.1 Acquirers' merger motives

The literature offers several non-mutually exclusive explanations for why firms initiate or consider mergers (e.g., Haleblian, Devers, McNamara, Carpenter, and Davison 2009).

Executive characteristics can influence merger decisions. Some executives prioritize personal interests over shareholder value (e.g., Trautwein 1990).[8] In firms with excess free cash flow, executives may engage in empire-building through acquisitions, thereby increasing their compensation and extracting rents from overseeing larger organizations (Jensen 1986). Supporting this view, Harford (1999) finds that cash-rich firms are more likely to pursue acquisitions. The hubris hypothesis (Roll 1986) further posits that executives may undertake mergers based on overly optimistic assessments of synergies. Subsequent studies confirm that managerial hubris can influence decisions such as acquisition price premiums (e.g., Hayward and Hambrick 1997).

Stock market misvaluations of firms' fundamentals also play a role. Acquirers with overvalued equity tend to target firms with less overvalued or undervalued stocks, typically using stock as payment (Shleifer and Vishny 2003; Dong, Hirshleifer, Richardson, and Teoh 2006; Gu and Lev 2011). According to Shleifer and Vishny (2003), when the stock market misprices firms' fundamental values and when acquirers possess superior information about their true value, the value of potential target firms, and the expected gains from a possible merger, these informed acquirers may exploit market misvaluations by acquiring undervalued or less overvalued target firms at favorable prices, thereby mitigating the impact of future stock price corrections. While

[8] Anand and Singh (1997, 104) argue that mergers between firms operating related businesses are less vulnerable to managerial self-interest, as "issues of bounded rationality, absorptive capacity and the compatibility of organizational routines are likely to be less acute in acquisitions involving similar firms with overlapping businesses."

these mergers may result in negative short- and long-term stock performance for the acquirers, they may still be better off compared to forgoing the acquisitions.

Some mergers serve as discipline mechanisms for ineffective management, consistent with the Q theory of mergers (Jovanovic and Rousseau 2002). Acquirers with stronger managerial capabilities can redeploy the assets of poorly governed firms more efficiently (Lang, Stulz, and Walkling 1989; Servaes 1991), especially when their managerial skills are transferable (Wang 2018). Wang and Xie (2009) find that the market assigns greater value to mergers with wider gaps in corporate governance quality, as measured by the G-Index (Gompers, Ishii, and Metrick 2003).

Research on merger waves highlights the role of exogenous economic shocks, suggesting that mergers serve as adaptive responses to changes in the business environment (e.g., Ravenscraft 1987; Shleifer and Vishny 1990). For instance, technological advancements can catalyze industry-wide merger activity (Harford 2005). Ahern and Harford (2014) show that such waves propagate through supply chain relationships. However, sufficient market-wide financial liquidity, such as low interest rates or a bull market, is a necessary precondition for merger waves (Rhodes-Kropf and Viswanathan 2004; Harford 2005).

Acquirers frequently cite synergies as a primary motive. In synergy-driven mergers, both firms aim to integrate resources and optimize control to maximize firm value (Dyer et al. 2024). Chatterjee (1986) categorizes synergies into anti-competitive market power, financial synergies, and operating synergies. Anti-competitive market power arises when reduced competition enables the merged firm to exert greater control over the supply and pricing of the products it offers (e.g., Eckbo 1983; Fee and Thomas 2004; Fathollahi, Harford, and Klasa 2022). Financial synergies include corporate tax advantages and co-insurance benefits due to improved capital structures (Leland 2007; Almeida, Campello, and Hackbarth 2011), risk diversification (Amihud and Lev 1981), and internal capital market efficiencies (Hubbard and Palia 1999). Operating synergies result from more efficient operations, leading to increased net operating cash flows post-merger, and are further detailed below.

Transaction cost theory posits that mergers occur when internalizing transactions is more efficient than market-based exchanges (Coase 1937; Grossman and Hart 1986). Several scenarios illustrate when mergers can improve cost efficiency. Firms can reduce hold-up risks by acquiring strategic business partners (Klein 1996), gain timely insights into upstream pricing by acquiring

suppliers (Arrow 1975), or stay responsive to customer demands through forward integration (e.g., Dyer et al. 2024). Both forward and backward integration can enhance bargaining power in supply chain transactions. Merging with firms operating related businesses may also yield economies of scope and scale (Sheen 2014). Grullon, Larkin, and Michaely (2019) argue that enhanced market power has become a more prominent source of value creation amid rising industry concentration in the U.S. over the past two decades. They find that increased profitability primarily stems from higher profit margins rather than improved efficiency.

Additionally, some firms pursue mergers as part of their ongoing search for growth opportunities (Levine 2017). Growth can stem from enhanced customer loyalty (Narayandas 2005), entry into new markets (i.e., access to new customer bases), or the acquisition of innovative resources and capabilities (Bena and Li 2014; Yu, Umashankar, and Rao 2016). For example, Hoberg and Phillips (2010) provide evidence that firms merge to achieve greater product differentiation.

2.1.2 Target firms' merger motives

Prior studies identify three primary motives for target firms to initiate a sale. Financial distress may prompt a firm to sell to avoid bankruptcy and preserve shareholder value (Masulis and Simsir 2018). Two additional factors may facilitate such sales: pressure from institutional investors advocating swift action and executive compensation incentives, such as golden parachutes (Fidrmuc and Xia 2019; Zha Giedt 2022).

Also, a mismatch between a firm's growth opportunities and its available resources can motivate a sale (Palepu 1986; Wang 2018). For instance, a firm developing promising pharmaceutical products may lack the capital or commercialization infrastructure to realize revenue growth. In such cases, a merger provides a strategic solution to address the growth-resource mismatch and enhance shareholder value. However, Dhaliwal et al. (2016) report a negative association between this mismatch, captured by a dummy control variable, and the likelihood of receiving takeover bids. A potential explanation for this contradiction is the evolving nature of merger synergies. Dessaint, Eckbo, and Golubov (2021) argue that synergies increasingly arise from redeploying target firm resources that complement unique, acquirer-specific assets. Consequently, firms with valuable assets may attract acquisition interest even without a growth-resource mismatch (Song and Walkling 2000; Chen, Miao, and Valentine 2022).

Executive retirement considerations may influence a firm's decision to sell (Ravenscraft 1987; Jenter and Lewellen 2015). Jenter and Lewellen (2015) argue that CEOs nearing retirement forgo less personal wealth when accepting a takeover offer compared to younger CEOs. Anecdotal evidence further suggests that selling the company may be preferable to navigating succession planning for some firms, such as those with founder CEOs.[9] Firms led by near-retirement CEOs are therefore more likely to consider a sale. Jenter and Lewellen (2015) find a significant and positive effect of CEOs aged 64–66 on the likelihood of a firm becoming a target, though the effect is weaker in firms with strong corporate governance.

Despite these motivations, target CEOs may resist takeovers to preserve personal benefits associated with leading a firm, either privately before a bid becomes public or during contested offers. Merger completion often diminishes the personal wealth and future career prospects of target CEOs (Hartzell, Ofek, and Yermack 2004). Although private rejection of undisclosed bids remains difficult to study due to data constraints, Bates and Becher (2017) find that the likelihood of rejecting a bid declines as the offer price premium increases. After controlling for bid quality, they report that personal gains of target CEOs from completed mergers do not affect merger completion, but are positively associated with the likelihood of upward bid revisions. Their findings suggest that target CEOs in contested bidding environments are unlikely to reject favorable offers.

2.1.3 Other factors affecting merger partner selection

After initiating a deal, firms often evaluate multiple potential merger partners before announcing a definitive merger agreement (Boone and Mulherin 2007; 2009; Welch et al. 2020). While certain factors may not directly motivate the initiation of a merger, they can shape the selection of merger partners and influence which pair of firms ultimately completes a merger.

The literature highlights the role of private information conduits in shaping merger likelihood. For example, interlocked directors (Cukurova 2012), shared lead bank lenders (Chen et al. 2021; Fee et al. 2019), common institutional shareholders (Brooks et al. 2018), and auditors with broad client bases (Xie, Yi, and Zhang 2013; Dhaliwal et al. 2016) can increase the probability of a merger. Rousseau and Stroup (2015) find that firms are more likely to acquire companies

[9] For a practical discussion of business exit strategies, see https://www.bdc.ca/en/articles-tools/change-ownership/plan-succession/3-common-exit-strategies (accessed in May 2025).

where their directors have previously worked. In contrast, Agrawal et al. (2013) show that, in recent decades, merging firms have become less inclined to engage the same financial advisors.

Industry dynamics and market conditions also shape merger partner selection. Afrin, Kim, Roychowdhury, and Yost (n.d.) find that suppliers are less likely to pursue forward vertical mergers when their customers face intense product-market competition. Rogan and Sorenson (2014) report that the likelihood of a merger increases with the number of shared clients between firms. Capital availability is another key factor, as firms with greater financial resources are more likely to pursue acquisitions (Celikyurt, Sevilir, and Shivdasani 2010; Chatterjee, Hasan, Kose, and An 2021). Firm performance also affects merger dynamics. Ali, Kravet, and Li (2016) find that firms with high industry-adjusted ROA are more likely to receive takeover offers when profitable, but less likely when incurring operating losses. Akdoğu, Paukowits, and Celikyurt (2023) report that firms with restrictive bond covenants are more likely to become takeover targets.

This study extends the literature on merger motives and contributes to research on merger completion by examining whether acquirers' value-creation motives influence target selection.

2.2 Related Mergers, Interfirm Similarity, and Merger Outcomes

2.2.1 Related mergers and interfirm similarity

Research on interfirm similarity in M&As originates from comparisons between related and unrelated mergers (e.g., Singh and Montgomery 1987; Harrison et al. 1991). According to the Federal Trade Commission (FTC) Merger Guidelines, resources are considered related when they include products, services, or distribution channels that competitors use to challenge a firm's market share or profitability (FTC 2023). Based on this classification, mergers that are vertical or horizontal, expand product portfolios, or extend geographic markets are defined as related, while conglomerate mergers are categorized as unrelated (e.g., Lubatkin 1983; 1987; Seth 1990a). In related mergers, firms share similarities in product or geographic markets or innovative resources. In contrast, in unrelated mergers, such similarities are minimal or absent.

Although no theory claims that related mergers consistently generate higher economic value than unrelated ones (Seth 1990b), the two are generally associated with different types of synergies: operating synergies in related mergers and financial synergies in unrelated ones (Seth 1990a). Research on merger value creation investigates whether firms should prioritize one form

of synergy over another, based on their existing resources and strategic objectives (Chatterjee 1986).

Three arguments have historically supported the view that related mergers outperform unrelated ones. First, Morck, Shleifer, and Vishny (1990) suggest that unrelated mergers are more prone to managerial motivations that fail to maximize shareholder value. Second, some studies argue that related mergers can achieve both operating and financial synergies, whereas unrelated mergers are generally limited to financial synergies (e.g., Lubatkin 1983; Singh and Montgomery 1987). Third, the higher frequency of related mergers implies that acquirers perceive greater value-creation potential in them (Seth 1990b). Nonetheless, empirical findings on whether related mergers outperform unrelated mergers remain mixed (e.g., Chatterjee 1986; Lubatkin 1987; Singh and Montgomery 1987; Morck et al. 1990).

Seth (1990b) identifies several reasons for these inconsistent findings. First, studies often apply different measures of value creation: some focus on acquirer shareholder wealth, while others assess synergy value, defined as the excess value of the combined firm over the sum of the stand-alone entities. While the former considers the share of synergy value allocated to the acquirer, the latter measures the total synergy generated. Second, variations in sample selection, such as industry mix, periods, firm size, and the inclusion of large gain or loss deals, affect the composition of related versus unrelated mergers and thereby influence observed shareholder wealth effects. Third, not all mergers are motivated by synergies, introducing noise unrelated to merger type (i.e., related versus unrelated). Finally, different categorization schemes, such as FTC-based versus industry-based typology, lead to inconsistencies in classifying related mergers.

The literature generally agrees that distinct mechanisms drive different sources of value creation. For instance, Seth (1990b) notes that vertical mergers involve firms with differing business models and logistics resources. Similarly, Seth (1990a) notes that economies of scale in related mergers depend on commonalities in product lines and logistics functions, including production and distribution.

Harrison et al. (1991) find that interfirm similarities affect value creation differently in related and unrelated mergers. Specifically, in same-industry mergers, similarities in capital expenditure, selling, general, and administrative expenses (SG&A), and interest expense intensities are negatively associated with long-run performance. In cross-industry mergers,

similarities in SG&A and research and development (R&D) intensity have a negative impact. Based on these results, the authors advocate moving beyond a dichotomous categorization of related and unrelated mergers, focusing instead on specific sources of value. King et al. (2004) similarly recommend examining determinants of merger performance within, rather than between, subgroups of related and unrelated mergers, emphasizing that performance variation arises primarily from within subgroups.

Several studies have explored interfirm similarity in innovation-driven mergers (e.g., Makri, Hitt, and Lane 2010; Bena and Li 2014; Yu et al. 2016). Bena and Li (2014) find that technological proximity increases the likelihood of mergers aimed at acquiring innovation-related resources. This relationship is largely driven by absorptive capacity, which enables firms to integrate complementary technological capabilities and promote knowledge creation (Bena and Li 2014; Yu et al. 2016).

Other studies examine how specific dimensions of interfirm similarity influence merger probability and performance. Ramaswamy (1997) reports that mergers between banks with similar competitive advantages result in better post-merger profitability. DeLong (2001) finds that mergers between banks with both similar economic activities and geographic proximity yield higher collective shareholder value. Lee, Mauer, and Xu (2018) argue that human capital similarity increases merger likelihood in unrelated mergers but decreases it in horizontal mergers. They contend that in unrelated mergers, human capital similarity enables firms to eliminate redundant labor, thereby enhancing value creation.

2.2.2 Product similarity

Some mergers aim to achieve product-market synergies by enhancing product differentiation (Hoberg and Phillips 2010), acquiring innovation resources for new product development (Bena and Li 2014), improving production efficiency (Sheen 2014), or increasing market power (Fathollahi et al. 2022). Prior studies offer several rationales for predicting a positive relationship between product similarity and the likelihood of merger activity (Wang and Zajac 2007; Hoberg and Phillips 2010; Fathollahi et al. 2022).

First, Wang and Zajac (2007) argue that firms seeking to cross-deploy each other's product resources may choose between forming alliances and pursuing acquisitions. Firms with high product similarity are more likely to opt for acquisitions than alliances. On the one hand, alliances

may be undermined by competing interests, particularly among close product-market rivals. On the other hand, alliances are generally preferred when information asymmetry is high, given the irreversible nature of acquisition investments. Close product-market peers tend to face lower information asymmetry (Bernard, Blackburne, and Thornock 2020) due to the knowledge accumulated throughout business operations, making acquisitions more attractive. Consistent with this reasoning, Wang and Zajac (2007) find that firms with high product similarity prefer mergers over alliances as a means to share and deploy resources and capabilities.

Second, Hoberg and Phillips (2010) propose that product similarity signals asset complementarity, which facilitates effective resource redeployment and post-merger product differentiation. They argue that firms exhibiting high product similarity with a broad set of firms possess wider product portfolios and stronger absorptive capability, both of which enhance merger likelihood (Mitchell and Shaver 2003). However, when product similarity is high among close product-market peers, it may indicate product substitutability, which discourages mergers and favors arm's length transactions (Afrin et al. n.d.). Hoberg and Phillips (2010) find that firms with high average product similarity to a broad set of firms are more likely to engage in mergers or asset acquisitions, whereas those with high similarity to close peers are less likely to do so.

Further, Hoberg and Phillips (2010) document descriptive statistics that actual merging pairs exhibit higher pairwise product similarity than randomly paired firms. They also find that product similarity between merging firms correlates positively with post-merger improvements in return on assets (ROA), sales growth, and new product introductions, supporting the asset complementarity argument. However, their study does not directly test the effect of pairwise product similarity on merger likelihood.

Third, Fathollahi et al. (2022) contend that horizontal mergers between firms offering similar products in concentrated industries enhance post-merger market power. They find a positive association between industry-average product similarity and the likelihood of horizontal mergers, particularly in highly concentrated industries.[10]

Lastly, Bena and Li (2014) suggest that firms may acquire product-market peers to access innovation resources, thereby supporting new product development and mitigating competition in

[10] They define horizontal mergers and measure industry-average product similarity based on firms sharing the same 3-digit Standard Industrial Classification (SIC) codes.

future product launches. In such cases, the associated absorptive capacity may stem from product similarity rather than technological proximity, leading to a positive effect of product similarity on the likelihood of innovation-driven mergers. They document a positive main effect of product similarity on merger likelihood and a substitution relationship between product similarity and technological proximity in influencing merger likelihood.

In summary, while the literature supports a link between product similarity and merger activity, it does not fully address whether pairwise product similarity influences acquirers' target selection across different value-creation motives, particularly those related to operating synergies where product-market resources are critical to value creation.

2.2.3 Geographic proximity

Prior studies identify two primary mechanisms through which geographic proximity influences merger outcomes: by generating operating synergies and by reducing information asymmetry. This subsection reviews relevant studies and situates the present study within this literature.

The synergy mechanism underlying geographic proximity

Several studies report a positive relationship between geographic proximity and merger value creation, attributing this association to synergy-generation mechanisms. Spiller (1985) uses the geographic proximity of vertically related firms' plants as a proxy for asset specificity, arguing that asset specificity enhances the value of vertical mergers, particularly when firms making specialized investments face potential opportunistic behavior from business partners (Klein 1996). Consistent with these arguments, Spiller finds a positive relationship between geographic proximity and the expected synergy value.

DeLong (2001) shows that bank mergers involving both geographic proximity and similar business operations reflect a focused growth strategy, yielding greater combined shareholder value than other bank mergers. According to DeLong, such focused bank mergers create value through improved cost efficiency, increased market position, and reduced overinvestment. Houston, James, and Ryngaert (2001) utilize branch-level data to measure the degree of geographic market overlap between merging banks and find a positive association between the extent of geographic market overlap and the NPV of acquirers' expected gains from the merger.

The information mechanism underlying geographic proximity

Uysal, Kedia, and Panchapagesan (2008) propose that geographic proximity improves acquirers' merger outcomes by enhancing access to private information about target firms, thereby enabling more effective identification of potential synergies. This informational advantage deters competition from distant bidders, increases the likelihood that geographically proximate acquirers capture a large share of acquirer-specific gains, and reduces the risk of the winner's curse. Their empirical findings support these claims, revealing a positive association between geographic proximity and acquirers' CARs. The authors further argue that these higher CARs are not driven by a higher prevalence of related mergers among mergers involving geographically proximate firms, as unrelated mergers between geographically close firms do not underperform related ones in terms of acquirer CARs.

Kang and Kim (2008) investigate block equity investments without control transfers and contend that geographic proximity reduces information acquisition costs and enables more effective post-investment oversight. Their findings indicate that proximity is positively associated with acquirers' governance involvement, targets' CARs, and targets' post-investment performance, especially when targets are characterized by high information opacity.

Chakrabarti and Mitchell (2013) find that geographic proximity increases the likelihood of mergers, particularly related mergers. In a later study, Chakrabarti and Mitchell (2016) argue that geographic distance acts as an information barrier, as differences in institutional environments and local consumer demographics across regions often necessitate location-specific market strategies. They further assert that evaluating related mergers requires more information than unrelated ones due to the greater complexity of post-merger integration. Consequently, firms may lack the necessary information to accurately assess the value of related mergers involving geographically distant partners at the time of the announcement. Although they do not identify a significant main effect of geographic distance on the completion probability of announced deals, Chakrabarti and Mitchell (2016) report a significant and negative interactive effect of geographic distance and related mergers in predicting merger completion, conditional on announced mergers.

Bick, Crook, Lynch, and Walkup (2017) argue that geographic proximity reduces the costs of information acquisition and processing between merging firms. They find that geographic

proximity shortens the time from merger announcement to completion, particularly for small targets. However, this effect diminishes after 2004.

In summary, the literature provides consistent evidence that geographic proximity enhances merger outcomes through both synergy-generation and information-reduction mechanisms. It plays a significant role in vertical and banking mergers and affects acquirers' CARs, post-investment governance involvement, the likelihood and completion of deals, and time to completion. This study contributes to the literature by offering new empirical evidence on how geographic proximity influences target selection across different value-creation motives. It also sheds light on how proximity interacts with alternative information sources to shape the likelihood of mergers, deepening our understanding of the mechanisms underlying the observed positive relationship between geographic proximity and merger activity.

2.2.4 Resource quality similarity: Assortative matching in mergers and acquisitions

Acquirers typically select a target firm after identifying candidates with desirable resources (e.g., Wernerfelt 1984; Welch et al. 2020). Rhodes-Kropf and Robinson (2008) find that firms with closer market-to-book asset ratios (Tobin's Q, or Q) are more likely to merge in complementarity-driven mergers. In contrast, Jovanovic and Rousseau (2002) suggest that value creation occurs when high-Q acquirers purchase low-Q targets in substitution-driven mergers. Complementarity-driven mergers generate value by allowing firms to redeploy each other's resources, whereas substitution-driven mergers replace the target's inefficient resource management with the acquirer's superior management.

Rhodes-Kropf and Robinson (2008) demonstrate that firms with similar resource quality, as proxied by comparable Tobin's Qs, are more likely to engage in complementarity-driven mergers. These deals involve distinct yet complementary resources that require integration to realize synergies. Their model posits that total synergies increase with partner quality, but the share of synergy captured by a firm decreases as the partner's quality rises. This tradeoff leads firms to prefer partners of similar quality to maximize expected net gains, a pattern described as positive assortative matching (Shimer and Smith 2000).

A necessary condition for positive assortative matching is low search friction in identifying merger partners. Under frictionless search, firms are optimally matched by quality: the highest-quality firms pair with each other, the second-best with the second-best, and so on (Shimer and

Smith 2000). When search frictions exist, firms tend to merge with those within their informational reach, rather than strictly by resource quality rank. Rhodes-Kropf and Robinson (2008) find that Q similarity is positively associated with merger likelihood only when search frictions are low. Using favorable macroeconomic conditions as alternative proxies for low search cost conditions, they find supporting evidence. Subsequently, Chen et al. (2021) provide micro-level empirical support, showing that firms connected through a common lead lender, thus searching within a low-search cost network, are more likely to merge when their Tobin's Qs are similar.

Rhodes-Kropf and Robinson (2008) acknowledge limitations in their analysis. They do not identify firm-level characteristics driving Q similarity, nor do they examine the conditions that may influence the tradeoff between synergy creation and distribution. As they state, "market reactions are an interesting but difficult place to look to understand why mergers are occurring or the value they are creating" (Rhodes-Kropf and Robinson 2008, 1201). They also suggest further exploration into the value implications of positive assortative matching. Inferred from their study is that this matching pattern may hold only when desired resources are relatively scarce and multiple potential targets possess such resources, an assumption yet to be empirically tested.

Kaul and Wu (2016) shift the focus from using Q as a proxy for resource quality to using productivity as a measure of a target's resource-utilization capability. Their theory suggests that acquirers prefer high-productivity targets when acquiring new but related resources, and low-productivity targets when acquiring identical resources. Empirical analysis of manufacturing mergers supports this proposition: acquirers pursue high-productivity targets when entering new geographic markets and low-productivity targets when penetrating existing ones.

In summary, prior research indicates that acquirers assess resource quality similarity differently depending on whether a merger is driven by complementarity or substitution. Prior studies often verify the complementarity versus substitution claim based on the observed association of interest. This study contributes to the empirical literature by examining how resource quality similarity influences target selection across varying value-creation motives related to operating synergies. Additionally, it examines whether the substitutability of target resources moderates the relationship between resource quality similarity and merger likelihood, thereby extending the empirical testing of positive assortative matching theory. It also examines the co-

occurrence of positive and negative assortative matching when both complementary and substitute resources might have contributed to mergers' value-creation.

2.3 Interfirm Similarity and Information Asymmetry

Identifying, evaluating, and selecting an appropriate target with the potential to generate operating synergies are critical steps in the merger process. Chakrabarti and Mitchell (2016) argue that assessing potential synergies in related mergers often requires soft information, such as cultural compatibility, due to the complexities of post-merger integration. The acquirer's ability to collect and process both hard and soft information about potential targets significantly influences target selection (e.g., Schildt and Laamanen 2006; Rhodes-Kropf and Robinson 2008).

Schildt and Laamanen (2006) find that firms tend to acquire targets with which they are already familiar. They show that prior alliance experience, technological knowledge overlap, and geographic proximity increase the likelihood of a merger. Similarly, Bettinazzi, Miller, Amore, and Corbetta (2020) find that ownership similarity raises merger likelihood, attributing this effect to the bounded information-processing capacity of strategic decision-makers, who tend to favor targets with information that is less costly to acquire and evaluate.

Finkelstein and Haleblian (2002) argue that firms are more capable of evaluating potential targets within their own industry, where they possess greater operational knowledge and experience. Wang and Zajac (2007) support this view, showing that product similarity increases merger likelihood, in part because product-market peers are more adept at evaluating each other's fundamental value than firms with dissimilar products. This familiarity may stem from accumulated knowledge of industry dynamics, competitive environments, supply chains, and logistics. Bernard et al. (2020) further demonstrate that information acquisition between product-market peers is positively associated with subsequent merger activity. However, they find that this effect diminishes in mergers among firms with high product similarity, suggesting that close product-market peers may already possess substantial familiarity before initiating merger talks.

Financial reporting is also a critical source of information in merger partner selection (e.g., Skaife and Wangerin 2013). According to the Financial Accounting Standards Board's conceptual framework (FASB 2018), firms engaged in similar economic activities are expected to produce comparably structured financial statements. Prior research shows that financial statement comparability reduces information processing costs for various external users, including analysts

(De Franco, Kothari, and Verdi 2011), debt market participants (Kim, Kraft, and Ryan 2013), auditors (Zhang 2018), and potential acquirers (Chen, Collins, Kravet, and Mergenthaler 2018). Francis, Huang, and Khurana (2016) find that cross-border merger activity is positively associated with GAAP similarity, which they attribute to lower information acquisition costs. De Franco, Vasvari, Vyas, and Wittenberg-Moerman (2020) find that firms with similar characteristics, such as asset tangibility, tend to adopt comparable bond covenant structures. They argue that such comparability reduces information acquisition costs for bond investors, thereby lowering bond yields and attracting long-term bond investment.

In summary, the observed pattern in which firms with similar resources are more likely to merge may be explained, at least in part, by acquirers' preference for familiar targets that reduce information processing needs. This familiarity helps mitigate the risk of a value-destroying transaction. This study contributes empirical evidence to the information-based mechanism underlying the effects of product similarity and geographic proximity on merger likelihood.

2.4 Public Target Firms' Information Environment and Merger Outcomes

This section reviews research on how the properties of public target firms' information environment influence merger outcomes.[11]

2.4.1 Effect on merger likelihood

Prior studies find that target firms in M&As tend to employ more conservative accounting practices (Ahmed, Chen, Duellman, and Sun 2023) and are less likely to have restated their financial statements before the merger announcement (Amel-Zadeh and Zhang 2015), compared to firms that do not receive takeover offers.

2.4.2 Effect on the completion rate of announced mergers

Conditional on a merger attempt, target firms with higher financial reporting quality are more likely to complete a successful sale, whereas those with lower quality are less likely (Skaife and Wangerin 2013; Amel-Zadeh and Zhang 2015; Marquardt and Zur 2015). Skaife and Wangerin

[11] Some studies examine how acquirers' accounting quality affects merger outcomes (e.g., Erickson and Wang 1999). For instance, Kravet (2014) and Francis and Martin (2010) find that firms with more conservative accounting are less likely to pursue risky acquisitions and tend to complete more profitable mergers than those acquirers with less conservative practices. However, in studies focusing on the accounting quality of target firms, the acquirers' accounting quality typically remains statistically insignificant when included as a control variable.

(2013) suggest that acquirers may renegotiate the offer or withdraw from negotiations if post-announcement due diligence reveals adverse information about the target or the merger's prospects. Such outcomes are less likely when the target's pre-announcement financial reporting fairly represents its actual value.

2.4.3 Effect on deal structure

To mitigate valuation risk associated with opaque information about target firms, acquirers may employ various strategies once a potential merger is underway. These include conducting private negotiations to gather additional information (Skaife and Wangerin 2013; Marquardt and Zur 2015) and structuring deals with equity payments to share post-merger integration risks that could arise from the target's *ex-ante* undisclosed adverse information. Raman et al. (2013) find that higher cash-flow-based earnings quality in target firms is positively associated with the use of cash payments in non-hostile mergers.

2.4.4 Effect on target shareholder wealth effects

Ahmed et al. (2023) find that accounting conservatism in target firms is positively associated with CARs for both acquirers and targets around merger announcements. Conservative accounting, characterized by more timely loss recognition, reduces the likelihood of hidden underperforming assets (Francis and Martin 2010; Kravet 2014), thereby lowering the risk of post-merger integration failure.

Several studies measure information transparency through earnings quality, specifically the alignment between cash flows and accruals (Dechow and Dichev 2002; McNichols 2002; Francis, LaFond, Olsson, and Schipper 2005). McNichols and Stubben (2015) find that higher earnings quality in target firms is associated with lower CARs for targets but higher CARs for acquirers. Raman et al. (2013) similarly report a negative association between target firms' earnings quality and price premiums in non-hostile mergers, attributing it to reduced uncertainty about target firms' performance rather than diminished earnings manipulation. Additionally, Martin and Shalev (2017) find that the amount of firm-specific information incorporated into target stock prices is negatively associated with targets' CARs around merger announcements.

Multiple factors may explain the negative associations between target firms' information transparency and both price premiums and target CARs.[12] First, the stock market may undervalue firms with opaque information before the merger announcement (e.g., Amel-Zadeh and Zhang 2015). Upon the announcement, investors may interpret the acquisition as a signal of hidden value, leading to greater stock price reactions for opaque targets (Raman et al. 2013). Second, firms with less transparent financials, particularly those with proprietary assets such as in-process innovations, may offer higher synergy potential and thus command higher premiums (Raman et al. 2013). Third, acquirers may be more susceptible to overpayment or may easily justify thoughtless takeovers when target firms' information is opaque (McNichols and Stubben 2015). Fourth, opaque targets are more likely to attract multiple bidders (Marquardt and Zur 2015), prompting more aggressive offers. In such cases, the winning bidder may fall victim to the winner's curse, especially when the target firm's information is less transparent (McNichols and Stubben 2015; Martin and Shalev 2017).

Overall, these studies consistently document a negative relationship between target firms' information transparency and their CARs.

2.4.5 Effect on synergy generation

Martin and Shalev (2017) find that the amount of firm-specific information embedded in target stock prices is positively associated with the combined CARs of acquirers and targets around merger announcements. They argue that such information allows potential acquirers to estimate potential synergies more accurately. Acquirers anticipating higher synergies are more likely to offer higher prices, supporting the view that the accessibility of target firms' information enhances efficient capital allocation in the M&A market. The effect is less pronounced in same-industry mergers, where acquirers are more likely to possess superior, private information about target firms.

2.4.6 Effect of target firms' publicly available information in same-industry mergers

Research suggests that acquirers in same-industry mergers rely less on publicly available financial reports when evaluating targets. Raman et al. (2013) argue that industry expertise and private information channels allow these acquirers to evaluate target performance more effectively,

[12] Amel-Zadeh and Zhang (2015) use deal value multiples to analyze the impact of financial restatements on target firms' negotiation outcomes, considering that many factors may influence stock-return-based price premiums.

thereby reducing the influence of financial reporting quality on price premiums. Consistent with these arguments, they find that cross-industry mergers primarily drive the negative association between financial reporting quality and price premiums.

Perafán-Peña et al. (2022), using European data, examine whether the relationship between target firms' upward earnings management and price premiums differs between same-industry and interindustry mergers. They find a negative association between target firms' discretionary abnormal accruals and price premiums in same-industry mergers, but a positive association in interindustry deals. They attribute this contrast to greater familiarity with economic environments and the adoption of comparable accounting systems among firms in same-industry mergers, which allows for better evaluation of earnings quality and merger value.

2.4.7 Effect of accessibility to target firms' private information

Several studies demonstrate that acquirers' access to private information about target firms influences the likelihood and performance of mergers.[13] Research employing social network analyses suggests that private information flows throughout networks of interconnected firms. Firms occupying central positions in these networks typically access more timely or richer information than peripheral firms.

Some studies investigate how network connections influence the likelihood of mergers. Chen et al. (2021) find that firms connected by the same lead lenders are more likely to complete a complementarity-driven merger than those without such ties. Dhaliwal et al. (2016) report that the size of an auditor's client base is positively associated with the likelihood that a client receives a takeover offer. Singh and Schonlau (2009) find that firms occupying central positions in board networks are more likely to complete mergers, whether as acquirers or targets. Similarly, El-Khatib, Fogel, and Jandik (2015) find that CEOs with central positions in executive networks are more likely to undertake acquisitions.

Other studies provide mixed findings regarding the impact of network connections on shareholder wealth outcomes across various network relationships. On the one hand, some evidence indicates that such connections facilitate the identification of value-creating merger

[13] Acquirers access private information to evaluate potential merger gains or losses when the expected benefits of information acquisition exceed the associated costs (Povel and Sertsios 2014).

opportunities. For example, Cai and Sevilir (2012) find that the expected synergy value is higher in mergers where board members of the merging firms have previously served together on another board. Similarly, Chen et al. (2021) report that both the expected synergy and the NPV of acquirers' expected merger gains are higher in mergers involving firms with a common lead lender than in mergers of unconnected firms. Chaudhry, Kontonikas, and Vagenas-Nanos (2022) find that acquirers realize greater shareholder wealth gains when their financial advisors hold central positions in advisory firm networks.

On the other hand, Ishii and Xuan (2014) find that close connections between the two merging parties are negatively associated with both collective shareholder wealth and the acquirer's shareholder wealth. They suggest that firms attempting a merger may risk conducting reckless due diligence or may fail to search for alternative partners when their close connections indicate interest in a merger.

Additionally, interfirm connections influence the distribution of synergies between merging parties. Studies show that when the acquirer and target firm share a common director (Cai and Sevilir 2012), auditor (Dhaliwal et al. 2016), or lead bank lender (Fee et al. 2019; Chen et al. 2021), the acquirer tends to secure higher CARs and pay lower price premiums. These studies argue that information intermediaries may face conflicts of interest. To preserve employment or business relationships with the post-merger entity, which is typically the acquirer, these intermediaries may facilitate negotiations in the acquirer's favor.

Collectively, the literature suggests that greater accessibility to target firms' information increases the likelihood of mergers, particularly in cross-industry deals. This body of work also emphasizes the need to look beyond publicly available information to fully understand the role of target firms' information environment in related mergers. The present study finds that the opaqueness of publicly available information about target firms does not significantly influence the likelihood of related mergers driven by operating synergies. However, private information channels can affect acquirers' target selection.

CHAPTER 3 THEORY AND HYPOTHEIS DEVELOPMENT

3.1 Product Similarity, Geographic Proximity, and Merger Likelihood

Operating synergies arise from enhanced business operations, wherein resource integration improves cross-functional decision-making, leading to increased post-merger net operating cash flows (e.g., Seth 1990a). Following Rabier's (2017) typology, I define five value-creation motives related to operating synergies: (1) improving cost efficiency, (2) enhancing market position, (3) revenue growth through enriching product portfolios, (4) revenue growth through expanding into new geographic markets, and (5) revenue growth through acquiring innovation resources. This section introduces relevant theoretical frameworks and empirical evidence for each synergy motive, forming the basis for hypotheses concerning product similarity and geographic proximity.

Product markets, geographic markets, and innovation resources are critical to generating those operating synergies. This study emphasizes product similarity and geographic proximity rather than innovation proximity, because product and geographic market resources are potentially relevant across all five value-creation contexts. In contrast, innovation resources primarily pertain to innovation-driven mergers. Moreover, Bena and Li (2014) provide evidence on the role of innovation proximity in innovation-driven mergers.

Improving cost efficiency. This motive focuses on reducing the cost of transforming inputs into outputs through post-merger operational improvements. Transaction cost theory posits that firms merge when internalizing transactions is more cost-efficient than coordinating them via the market (Coase 1937; Grossman and Hart 1986).

Mergers may improve cost efficiency in several scenarios. First, acquisitions can resolve contractual inefficiencies in partnerships where one firm's outputs serve as critical inputs for the other, particularly when partner-specific investments are involved. Klein (1996) argues that under certain unforeseen, non-contractual conditions, enforcing the original contract may become prohibitively costly for one party while favoring the other. Disadvantaged firms may pursue acquisitions as a solution. Second, vertical acquisitions can enhance planning and coordination and reduce the bargaining power of the merging firms' supply chain partners (Dyer et al. 2024). For example, downstream firms may acquire upstream suppliers to access timely information on upstream prices for efficient production planning (Arrow 1975), while upstream firms may acquire

downstream customers to better understand end-consumer demand (Dyer et al. 2024). Third, related mergers can generate economies of scale and scope, facilitating cost synergies through resource sharing and operational integration (Teece 1980; Panzar and Willig 1981; Seth 1990a; Chavas and Kim 2010; Sheen 2014).

These studies suggest that mergers motivated by cost efficiency do not necessarily involve firms with similar products, depending on the relative composition of vertical and horizontal mergers. Vertical mergers typically involve dissimilar product offerings, while horizontal mergers, which entail scale and scope economies, tend to involve firms with similar product portfolios. Prior studies generally document a higher prevalence of same-industry mergers (e.g., 69% in Martin and Shalev 2017). In the current sample, 89% of mergers occur within the same industry. Therefore, I hypothesize that product similarity is, on average, positively associated with the likelihood of mergers motivated by improving cost efficiency.

Geographic proximity may further support the realization of synergies in such mergers by facilitating the cross-utilization of products and production resources while reducing redundancies (Spiller 1985). Thus, I also expect a positive relationship between geographic proximity and the likelihood of mergers focused on improving cost efficiency.

Enhancing market position. An enhanced market position results from an increased market share in product markets, geographic markets, or both by integrating two firms with overlapping markets. Merger announcements often note that the combined firm gains access to greater investment opportunities than either could pursue independently.[14] Govindarajan, Lev, Srivastava, and Enache (2019) document growing disparities in investment opportunities between large and small firms over the past two decades. Similarly, Grullon et al. (2019) argue that, as U.S. industries have consolidated, market power has become an increasingly significant source of value creation. Their findings suggest that the link between industry concentration and profitability is

[14] For example, the announcement of a definitive merger agreement between *Tellabs and AFC* states: "Together, Tellabs and AFC create a strategic global telecom equipment supplier that will lead the industry's shift to broadband data with end-to-end access and transport solutions …. Marrying the leader in access with the leader in transport positions us to grow with our customers in the industry's sweet spot of broadband services."
See https://www.sec.gov/Archives/edgar/data/317771/000031777104000044/ex99_1.htm.
For another example, the *Hewitt and Exult* merger announcement states: "Following the merger, Hewitt will be the global leader in the rapidly growing HR business process outsourcing (BPO) industry with enhanced growth prospects. It will be the only organization capable of offering total HR BPO services … on an integrated basis with complete HR consulting expertise."
See https://www.sec.gov/Archives/edgar/data/1168478/000104746904020788/a2138727zex-99_1.htm.

primarily driven by firms' ability to command higher profit margins rather than by gains in operational efficiency.

These insights indicate that both product similarity and geographic proximity between merging firms positively influence the likelihood of mergers aimed at enhancing market position.

Acquiring revenue growth. Revenue growth following a merger may arise from: (1) cross-selling products and offering newly bundled solutions to the combined customer bases; (2) entering new geographic markets and deepening penetration in overlapping ones; and (3) acquiring patented or non-patented innovation resources that enable new product development (e.g., Chartier, Liu, Raberger, and Silva 2018; Rabier 2017).

Revenue growth—enriching product portfolios. Acquirers may expand their product or service offerings to meet customer needs more effectively and enhance differentiation from product-market competitors. For example, *Cisco Systems Inc.* acquired *Scientific-Atlanta Inc.* for approximately $6.9 billion to address the rising demand for advanced information and entertainment services. According to the merger announcement, the deal would allow them to "address more quickly the growing number of opportunities … [and] create new products and services that might not have existed otherwise" (Cisco Newsroom 2005). Therefore, acquirers typically target firms possessing some related but dissimilar products from their own, seemingly suggesting a negative effect of pairwise product similarity on merger likelihood.

However, many U.S. public firms offer a mix of products, some dissimilar from the acquirer's product portfolio (the products sought by acquirers) and other products, which could be similar to the acquirer's offerings. Hoberg and Phillips (2010) find that in product differentiation-driven mergers, higher pairwise product similarity is positively associated with improvements in ROA, sales growth, and the length of product descriptions capturing new product offerings. They attribute this positive relationship to high asset complementarity between firms offering similar products, resulting in the acquirer's strong integration capacity to realize post-merger product differentiation synergies. Therefore, building on their arguments and findings, I hypothesize that in mergers seeking to enrich product portfolios, higher product similarity increases the likelihood of merger completion.

Although geographic proximity is irrelevant to product portfolios, it may increase the favorability of a particular target candidate among otherwise comparable ones due to the potential

benefits from cost synergies and market position enhancement synergies, as illustrated above. Therefore, I hypothesize a positive relationship between geographic proximity and the likelihood of mergers focused on enriching product portfolios.

Revenue growth—expanding into new geographic markets. Acquirers may pursue geographic expansion to access new customer bases.[15] Approximately 80% of mergers motivated by geographic expansion involve bank mergers. Geographic markets are central to banks' growth strategies (e.g., Kim and Finkelstein 2009), as demonstrated by the history of branching deregulation (e.g., Jayaratne and Strahan 1997).[16] Banks often gradually expand by entering adjacent counties or metropolitan statistical areas (MSAs), leveraging their familiarity with regional demographics and competition landscapes. Target banks in such expansions may also share overlapping markets with the acquirers (Houston et al. 2001), entailing additional synergies from enhanced market presence. Moreover, expansion into nearby regions is cost-effective. Geographic proximity facilitates brand equity consolidation and lowers the information acquisition costs for potential customers evaluating the new bank's credibility (Carbo-Valverde, Perez Saiz, and Xiao 2025). Accordingly, I expect geographic proximity to be positively associated with the likelihood of mergers aimed at geographic expansion.

Both similar and dissimilar product portfolios can contribute to value creation in the context of geographic expansion. Acquirers may prefer targets with similar offerings to prevent brand dilution and simplify post-merger integration. Conversely, acquiring firms with dissimilar products may generate cross-selling opportunities across the expanded customer base. Nonetheless, DeLong (2001) finds that bank mergers characterized by both product similarity and geographic proximity outperform other bank mergers by excelling in focused markets. Given the predominance of bank mergers in this category, I expect that, on average, product similarity positively affects the likelihood of mergers driven by geographic expansion.

[15] This study focuses exclusively on domestic geographic expansion. Geographic market choices involving international strategies through cross-border mergers are beyond the scope of this analysis.
[16] Outside of the banking industry, I am unaware of any directional discussions of domestic geographic expansion in other non-utilities sectors. I draw on bank branching deregulation because acquirers often appreciate the geographic presence of acquired banks when announcing definitive agreements.

Revenue growth—acquiring innovation resources. Firms may pursue mergers to acquire in-process R&D and patented innovations, thereby sustaining the competitiveness of their offerings and enhancing customer loyalty.

The similarity in commercialized products appears less relevant. However, Bena and Li (2014) suggest that firms may acquire product market peers to access innovation resources targeting overlapping customer bases, facilitating the development of new offerings and eliminating future competition. Besides incentives, they argue that firms in the same product market can effectively integrate others' innovation resources, given the absorptive capacity developed through product-market competition. They find supporting evidence of a positive relationship between product similarity and the likelihood of innovation-driven mergers. Building on their findings, I expect product similarity to positively correlate with the likelihood of innovation-driven mergers.

Geographic proximity is less relevant to innovation advancement but may influence acquirers' awareness of other firms' innovation resources by acting as an information conduit (Schildt and Laamanen 2006). However, firms often search for innovation resources beyond their local reach, utilizing other information channels such as inventor mobility (Rosenkopf and Almeida 2003). Therefore, I do not expect geographic proximity to affect the likelihood of innovation-driven mergers.

Reduced information asymmetry. Beyond the five value-creation channels, both similarity dimensions can increase merger likelihood because of reduced information asymmetry between close product market peers and geographically proximate firms, respectively. Strategic decision-makers, constrained by bounded rationality, tend to rely on information that is easier to obtain and process (Schildt and Laamanen 2006; Bettinazzi et al. 2020). Prior studies show that firms with greater product similarity face lower information asymmetry in merger evaluations (Wang and Zajac 2007; Bernard et al. 2020). Such familiarity may stem from operational experience and market monitoring, which provide insights into industry dynamics, supply chains, logistics, and other relevant aspects.

Similarly, geographic proximity can influence merger outcomes by reducing information asymmetry between firms (e.g., Chakrabarti and Mitchell, 2013; 2016; Bick et al. 2017). Uysal et al. (2008) argue that local acquirers gain superior access to private information about targets,

enabling them to identify potential synergies more effectively than acquirers distantly located. This information advantage, widely recognized, discourages aggressive bids from distant acquirers. Consequently, local acquirers are more likely to capture a larger share of acquirer-specific synergies and avoid the winner's curse compared to distant acquirers, thereby increasing their chances of completing the merger.

In summary, I hypothesize that product similarity is positively associated with the likelihood of operating synergy-driven mergers across various value-creation motives. The hypotheses, stated in the alternative format, are as follows.

> **Hypothesis 1a (H1a).** *Product similarity is positively associated with the likelihood of mergers aimed at operating synergies.*

> **Hypothesis 1b (H1b).** *The positive relationship between product similarity and merger likelihood is significant across mergers driven by different value-creation motives related to operating synergies.*

I also hypothesize that geographic proximity positively influences the likelihood of operating synergy-driven mergers and that the positive relationship between geographic proximity and merger likelihood holds across value-creation motives, but not for innovation-driven mergers.

> **Hypothesis 2a (H2a).** *Geographic proximity is positively associated with the likelihood of mergers aimed at operating synergies.*

> **Hypothesis 2b (H2b).** *The positive relationship between geographic proximity and merger likelihood is insignificant for innovation-driven mergers but significant for mergers driven by other value-creation motives related to operating synergies.*

3.2 Resource Quality Similarity and Merger Likelihood

Acquirers typically select target firms from a pool of candidates possessing the resources required to fulfill specific value-creation motives (e.g., Wernerfelt 1984; Welch et al. 2020). These target candidates likely vary in resource quality, defined here as a firm's effectiveness in leveraging its collective resources for current and future profits. The collective resources include products, managerial skills, market share, and other relevant assets.

Given multiple target candidates, rational acquirers choose targets that maximize expected net gains, determined by the synergy potential from integration and the share of synergy they can retain (Wernerfelt 1984; Rhodes-Kropf and Robinson 2008). Rhodes-Kropf and Robinson (2008) prove that when an acquirer seeks complementary resources, total synergy potential increases with the target's resource quality, while its bargaining power decreases, lowering the share of synergy it can retain. When search frictions are low, acquirers maximize net gains by balancing total synergy potential and synergy distribution, thereby favoring targets of comparable resource quality ranks, captured by Tobin's Q similarity, a pattern known as positive assortative matching (Shimer and Smith 2000; Becker 1973). I elaborate on the key elements of their theory to illustrate its applicability to the setting of related mergers aimed at operating synergies in the following paragraphs.

Rhodes-Kropf and Robinson (2008) suggest that search frictions may impede acquirers' ability to identify all relevant candidates and to make rank-order assessments of resource quality and associated gains. Accordingly, they expect the positive relationship to emerge only when search frictions are low. Prior studies suggest that the amount and quality of publicly available information about target firms matter less for acquirers when evaluating mergers within the same industry than across industries (Raman et al. 2013; Martin and Shalev 2017; Perafán-Peña et al. 2022). Moreover, various private information channels, such as exposure to similar product markets, geographic proximity, and shared networks (e.g., common auditors or closely connected boards), facilitate acquirers' identification of potential targets (e.g., Almazan, De Motta, Titman, and Uysal 2010; Cai and Sevilir 2012; Cai et al. 2016; Chakrabarti and Mitchell 2016; Dhaliwal et al. 2016; Bernard et al. 2020). I infer from these studies that acquirers in operating synergy-driven mergers face low search frictions in identifying potential targets.

Another necessary condition for positive assortative matching to emerge is that the two parties match on complementary resources. In operating synergy-driven mergers, both firms perceive opportunities to improve profitability by integrating complementary resources, thereby enhancing business operations and growth opportunities (Dyer et al. 2024). Building on acquirers and targets' self-perception of complementarity, I assume that operating synergy-driven mergers are, in essence, complementarity-driven. Therefore, resource quality similarity is expected to be positively associated with merger likelihood when search frictions are low.

A central assumption of their theory is that complementarity-driven mergers involve integrating scarce resources, resources obtainable only through mergers. Resource scarcity, in turn, implies heterogeneity in resource quality among potential target firms possessing the same assets. Such heterogeneity increases the likelihood that acquirers incur costs when they switch from one candidate to another in the pursuit of the same value-creation goal (Lentz and Mortensen 2010). In other words, acquirers will likely expect different merger gains when evaluating heterogeneous targets, making resource quality similarity versus dissimilarity a more salient determinant of target selection.

In summary, I hypothesize that resource quality similarity positively associates with the likelihood of operating synergy-driven mergers. Formally:

> **Hypothesis 3a (H3a).** *Resource quality similarity is positively associated with the likelihood of mergers aimed at operating synergies.*

Nonetheless, beyond target information opacity (e.g., Martin and Shalev 2017), search frictions can also arise from acquirers' cognitive constraints (e.g., Ishii and Xuan 2014) or from the opportunity costs of delaying merger decisions to evaluate all candidates (Rhodes-Kropf and Robinson 2008). Ishii and Xuan (2014) find that mergers are more likely when firms' boards have tight social connections, which may drive mergers due to familiarity rather than value-maximization considerations. Considering that the education and professional background of individuals working in the same or vertically related industries often overlap, variation in the strength of social connections between acquirers and potential target firms might be pronounced in related mergers. Such relational ties, combined with the possibility of competitive pressure from rival acquirers pursuing the same strategic resources, may elevate the costs of delaying merger decisions. Together, these factors could weaken or even obscure the expected positive association between resource quality similarity and merger likelihood.

Ex-ante, prior literature provides limited guidance on exceptions to the positive assortative matching pattern across different value-creation contexts related to operating synergies. Therefore, I hypothesize that the positive relationship between resource quality similarity and merger likelihood remains significant across mergers categorized by the five value-creation motives. Nonetheless, the distribution of the number of plausible target candidates possessing the necessary

resources to fulfill specific value-creation goals likely varies, which may influence the strength of this relationship. The hypothesis, stated in the alternative format, is as follows.

> **Hypothesis 3b (H3b).** *The positive relationship between resource quality similarity and merger likelihood is significant across mergers driven by different value-creation motives related to operating synergies.*

CHAPTER 4 RESEARCH DESIGN

4.1 Data and Sample Selection

The sample selection begins by identifying completed mergers between two U.S. public firms in related industries using the Refinitiv SDC Mergers & Acquisitions database (SDC) accessed via Wharton Research Data Services. To ensure that acquirers have fully considered the integration of target firms' resources in merger partner selection, I retain deals that meet the following criteria: (1) are classified by the SDC as "Merger" or "ACQ of Majority Interests"; (2) result in a change of control, where the acquirer owns less than 50% of the target's shares before the merger and seeks 100% ownership post-merger; and (3) involve significant value-at-stake for the acquirer, defined as a deal value exceeding either $10 million or 1% of the acquirer's market capitalization four weeks before the merger announcement. I also require the target's share price to exceed $1 four weeks before the merger announcement. The sample includes only completed deals with a non-missing effective date and excludes transactions classified as divestitures, repurchases, recapitalizations, restructurings, spin-offs, or acquisitions of subsidiaries.

Next, I retain only the first announced merger in cases of serial acquisitions, defined as five or more completed mergers by the same acquirer announced within three calendar years (Fuller, Netter, and Stegemoller 2002; Golubov, Yawson, and Zhang 2015). This restriction is motivated by two considerations. First, serial acquisitions often have a shared value-creation strategy. The search efforts are likely concentrated in the pre-deal phase of the first merger announcement, and the series of target firms likely possess similar resources. Including subsequent deals would weaken the power of testing the positive assortative matching theory (Rhodes-Kropf and Robinson 2008), as acquirers sequentially acquire multiple firms rather than select the single optimal match by weighing synergy potential against distribution. The target selection in the initial deal is more likely to reflect the tradeoff decision-making process than subsequent deals. Second, prior studies suggest that market reactions to subsequent deals in serial acquisitions differ systematically from non-serial acquisitions or initial deals in serial acquisitions (Croci and Petmezas 2009; Renneboog and Vansteenkiste 2019), potentially introducing noise in assessing shareholder wealth effects.

I require both the acquiring and target firms to have valid identifiers in the Compustat and CRSP databases, with single-class securities listed on the NYSE, AMEX, or NASDAQ. Mergers

are retained if both firms' fiscal years before the merger fall between 2003 and 2021, inclusive.[17] Further, I require both firms to have non-missing NAICSH codes in Compustat that can be mapped to U.S. Bureau of Economic Analysis (BEA) Input-Output (IO) industry codes.[18] I classify industries as vertically related if one industry purchases at least 5% of its inputs from the other or sells 5% or more of its outputs to the other, and vice versa (Haunschild 1993; 1994). I retain only mergers between firms in the same industry or vertically related industries (related mergers).

I further require valid BoardEx identifiers for both firms in the fiscal year preceding the merger announcement (i.e., at least one director's employment record indicates affiliation with the firm during that year). One benefit of this data requirement is to reduce the heterogeneity in governance structure factors that could otherwise confound the analysis of synergy considerations in merger decision-making. The second benefit is to improve the availability of managerial statements on value-creation motives, as such information is typically disclosed in joint press releases for material transactions. Third, this study examines board networks within related industries as a channel for private information flow (e.g., Cai and Sevilir 2012; Ishii and Xuan 2014) in operating synergy-driven mergers. I use the presence of connected boards to examine the information mechanism. After this step, the preliminary sample comprises 790 mergers.

To analyze acquirers' target selection, I require that each actual target firm be matched with at least one control firm. I then pair the actual acquirer with up to five control target firms to construct control mergers for each observed merger. Section 4.2 details the matching procedure. I exclude two mergers in which the acquirer later becomes a target within four months, yielding 573 actual mergers with at least one matched control merger. Requiring non-missing data for all explanatory variables reduces the sample to 555 actual mergers.

I then retain only mergers with an identifiable operating synergy motive. Specifically, I first exclude mergers where acquirers or target firms are in the oil, gas, and utilities industries, as firms in these industries often have regulated assets. I also exclude mergers where either party's

[17] I require that the pre-merger fiscal year begin in 2003 to ensure that target selection occurs after the enactment of the Sarbanes-Oxley Act of 2002 (SOX-2002), which substantially affected corporate governance and information environments. I also require a two-year post-merger observation window to evaluate long-term merger performance. Thus, mergers must be completed by 2021, and the pre-merger fiscal year must not extend beyond 2021.

[18] I convert Compustat NAICSH codes to IO industry codes using the 2012 concordance table of IO industry codes and NAICS codes provided by the BEA. Cross-year NAICS concordance tables are obtained from the U.S. Census Bureau. A summary file of cross-year industry code mappings is available upon request. Supplemental Material S1 defines vertically related industries and provides details on industry mapping procedures.

core business centers on project-based investments aimed at returns on investments (de Groote, Kleindienst, Hoegl, Schweizer, and Laamanen 2021).[19] Following Rabier (2017), I identify five value-creation motives related to operating synergies and use a double-coder process (described in Appendix C) to classify each merger based on hand-collected data, covering mergers announced through December 31, 2021. Mergers lacking identifiable synergy motives are excluded. The final sample for target selection analyses includes 459 actual mergers and 2,160 control mergers.

Table 1, Panel A, summarizes the sample selection criteria. Panel B presents the frequency distribution of the 459 sample mergers by acquiring and target firms' IO industry at the sector level.[20] The most merger-active sectors are Finance and Insurance, Durable Goods, Nondurable Goods, and Information. Non-tabulated data show that 89% of mergers occur within the same industry. Panel C reports the frequency distribution of the 459 sample mergers by the calendar year of merger announcements, based on the SDC data. Merger activity is relatively lower in 2005, 2009, 2011, and 2020, likely due to the Dotcom aftermath, the Great Recession, the U.S. debt ceiling crisis, and the COVID-19 pandemic, respectively. Panel D displays the sample distribution by acquirers' value-creation motives. The most common are enhancing market position (36%) and enriching product portfolios (31%).

4.2 Construction of Control Mergers

Control mergers are constructed by pairing each actual acquirer with up to five non-merging control target firms. Control target firms are selected using nearest-neighbor propensity score matching without replacement, based on firm characteristics from the fiscal year before the merger announcement. Propensity scores are estimated using a logit model that predicts the likelihood of firms becoming a merger target in the subsequent year: $Target = Size + BTM + BHAR + IndFE + YearFE$, where *Size* is the natural logarithm of the book value of total assets, *BTM* is the book-to-market ratio of equity, and *BHAR* is the annual buy-and-hold abnormal return at the fiscal year-end before the merger announcement.[21] The dependent variable equals one for actual target firm-

[19] de Groote et al. (2021, Appendix 1) identify SIC 4-digit codes representing industries where project investment is a core activity: 6798, 6799, 6211, 6719, 6726, 6722, 6552, and 1311.

[20] The BEA IO industry classification includes multiple levels of detail. At the sector level, there are 21 industries, and at the summary level, 71 industries, including government sectors. The frequency distribution of sample mergers is tabulated at the sector level, excluding government sectors. Control target firms are selected from non-merging firms within the same IO industry at the summary level.

[21] *Size* is defined as the natural logarithm of the book value of total assets (Compustat data item *AT*). *BTM* is the book-to-market equity ratio, calculated as *BE/ME*, where $BE = SEQ - PSTK$ and $ME = PRCC\_C \times CSHO$ (Compustat data

years and zero for potential control firm-years. Predicted propensity scores are saved for use in the matching process.

These three measures of matching criteria serve to mitigate the possibility that mergers are driven by factors other than operating synergies, which may also result in the observation of similarities between merging firms. Specifically, prior studies indicate that firms dissimilar along these dimensions are associated with distinct merger behaviors. First, large and small firms exhibit systematically different merger outcomes, even after controlling for other observable factors (Moeller, Schlingemann, and Stulz 2004; Alexandridis, Fuller, Terhaar, and Travlos 2013). Second, some mergers are motivated by stock market misvaluations, whereby overvalued acquirers tend to target undervalued or less overvalued firms (Shleifer and Vishny 2003; Dong et al. 2006; Gu and Lev 2011). Third, firm performance influences merger motivations. High-performing firms may acquire for managerial incentives (Jensen 1986; Roll 1986; Harford 1999), while poorly performing firms may sell under financial pressure (Masulis and Simsir 2018). Industry- and year-fixed effects control for merger clustering by industry and year (e.g., Mitchell and Mulherin 1996; Andrade, Mitchell, and Stafford 2001; Harford 2005).

The identification of potential control firm-years for the logit model proceeds in three steps. First, I retain all U.S. public firms with single-class securities listed on the NYSE, AMEX, or NASDAQ that have available data for the relevant firm characteristics. Second, I retain only firm-years within the industry-years represented by the 459 actual target firms in the year before the merger announcement. Third, I exclude firm-years in which the firm is involved in a merger, either as an acquirer or a target, during the three fiscal years ([t-2, t]) relative to the merger announcement year (t).[22] Using this dataset of potential control and actual target firm-years, I estimate propensity scores from the logit model.

Matching is then implemented as follows: (1) the control firm must operate within the same IO industry as the actual target firm in the fiscal year before the merger announcement; (2) the

items). *BHAR* is the annual buy-and-hold abnormal return as of the fiscal year-end prior to the merger announcement. I require at least six non-missing monthly returns over the 12-month period ending at the fiscal year-end.

[22] I assess whether the firm is an acquirer or a target firm in mergers that meet the following criteria based on SDC data: (1) the merger must be completed; (2) either the acquirer or the target firm must be a U.S. public firm with a non-missing CUSIP; (3) the acquirer must hold less than 50 percent of the target firm's equity and seek to own more than 50 percent post-merger; (4) the merger format must be "Merger" or "ACQ OF MAJORITY INTEREST"; and (5) both the merger announcement and effective dates must be available.

control firm's propensity score must fall within a caliper of 0.01 of the actual target's score; (3) the control firm's market capitalization must range from 30% to 300% of the actual target's market capitalization; and (4) up to five control firms with the nearest propensity scores to each actual target are retained without replacement. Only actual-control pairs with at least one matched control firm are retained. A post-matching assessment reveals no significant differences in *Size, BTM*, or *BHAR* between actual targets and their matched controls, indicating good covariate balance. Appendix B provides additional detail on the operationalization of these procedures.

4.3 Classification and Data of Value-Creation Motives

Following Rabier (2017), I classify operating synergy-driven mergers into five categories by value-creation sources: (1) improving cost efficiency, (2) enhancing market position, (3) enriching product portfolios, (4) expanding into new geographic regions, and (5) acquiring innovation resources. I infer the acquirers' merger motives primarily from their public announcements of definitive merger agreements, which typically appear as joint press releases issued by the merging firms. These press releases outline transaction terms, deal highlights, and executive commentary on expected strategic and financial benefits from the merger.[23]

In most cases, joint press releases are accessible via the SEC's EDGAR database. When such a release is unavailable or lacks a clear strategic intent, I consult supplementary sources, including conference call transcripts or presentation materials. If those are also unavailable on EDGAR, I conduct targeted web searches, beginning with the acquirer's investor relations or media section, and, if necessary, major news outlets such as Reuters. I manually extract statements that reflect the acquirer's rationale and objectives for the merger. To ensure the reliability of classification, I employ a double-coder and reconciliation process. Appendix C details the data collection process and classification methodology.

[23] The announcement date of a definitive merger agreement may differ from the merger announcement date recorded in SDC. For instance, in tender offers, SDC often codes the initial tender date as the announcement date, which may follow the target's rejection of negotiation. These initial tender announcements typically emphasize offer attractiveness to target firms' shareholders without disclosing expected synergies from the merger. I consider the announcement of a merger agreement to be the point when capital markets can reasonably evaluate the merger value. Accordingly, I manually collect the announcement dates of definitive merger agreements to examine shareholder wealth effects. However, I use the unadjusted SDC announcement date to analyze target selection, as it reflects when the acquirer discloses the selected target.

4.4 Key Independent Variables of Interfirm Similarity

Product similarity. I employ the product similarity measure (*SimPROD*) developed by Hoberg and Phillips (2010; 2016), which captures the cosine similarity between two firms' word choices in describing their product portfolios in 10-K Item 1 or Item 1A. Each year, Hoberg and Phillips generate a list of unique words from each firm's product description to represent its characterization of business activities. Higher *SimPROD* values indicate greater overlap in word choices, reflecting more similar product portfolios.

Take two cases with contrasting product similarity scores for illustration. A case with the lowest product similarity (*SimPROD* = 0.0023) in the sample appears between *AT&T* (NAICS: 517210) and *DIRECTV* (NAICS: 515210), a merger aimed at enriching product portfolios. *AT&T* emphasizes telecommunication services by business segment, including wireless and wireline data, voice, and other services. In contrast, *DIRECTV* highlights digital television entertainment services by geographic segment, providing digital television and satellite-based video programming to residential and commercial subscribers. These firms exhibit minimal overlap of word usage in product descriptions.

By contrast, a case with the highest product similarity (*SimPROD* = 0.6161) is observed between *FIRST BUSEY* (NAICS: 522110) and *FIRST COMMUNITY FINANCIAL PARTNERS* (NAICS: 522110), a merger focused on geographic expansion. Both are bank holding companies headquartered in Illinois, subject to similar regulatory disclosure structures, and each operates a single banking subsidiary that focuses primarily on loans and deposits.

Geographic proximity. Geographic proximity (*GeoProx*) is measured as the natural logarithm of one plus the geographic distance (in kilometers) between the headquarters of two firms (Chakrabarti and Mitchell 2016). The log transformation reduces skewness in the distribution of distance values, and the addition of one ensures that non-missing values are assigned to firms sharing the same zip code (i.e., distance equals zero). Headquarters locations are identified based on firm zip codes from Compustat, with distance computed using the Python library *pgeocode*.

Resource quality similarity. Following Rhodes-Kropf and Robinson (2008), this study measures resource quality similarity (*SimQ*) as the negative absolute difference in the natural logarithms of Tobin's Q between two firms. Resource quality is defined as a firm's effectiveness in leveraging its collective resources for current and future profits, as assessed by the capital market

and reflected in Tobin's Q.[24] The collection of resources may include products, managerial skills, market share, and other relevant assets. The calculation of *SimQ* is as follows.

$$\text{SimQ} = -|\ \ln(\text{AcqQ}) - \ln(\text{TrgQ})\ | = -|\ \ln(\text{AcqQ} / \text{TrgQ})\ |$$

The relationship of interest is whether an acquirer is more likely to select a target whose resource quality ranking is closer to its own within respective asset classes, among multiple potential targets featuring the same assets sought by the acquirer. Within matched groups of actual and control mergers, *SimQ* varies depending on the denominator—the Tobin's Qs of potential targets possessing the acquirer's desired assets. For firms with the same assets, variation in Tobin's Qs may reflect factors other than resource quality, such as market misvaluation or the size effect. Thus, concerns exist that variation in *SimQ* reflects differences in factors other than resource quality. The matching criteria for actual and control targets alleviate this concern by ensuring comparability on dimensions other than resource quality. Specifically, control target firms are drawn from the same industry as the actual target and matched on propensity scores of takeover likelihood, with an additional restriction on market capitalization relative to the actual target. In implementing PSM, actual and control targets are matched on total assets, book-to-market equity, and past-year stock return performance. In the following discussion, I provide additional intuition for why *SimQ* reasonably captures similarity in resource quality ranking between merging firms within respective asset classes under the theoretical framework of Rhodes-Kropf and Robinson (2008).

According to Rhodes-Kropf and Robinson (2008), Tobin's Q effectively captures resource quality among firms featuring the same assets, as Tobin's Q is assumed to be monotonically increasing in resource quality. Their model distinguishes two components of Tobin's Q for potential merger participants: investment Q and merger Q. Investment Q reflects the market value of a firm's assets relative to their book value. Firms with higher-quality assets are expected to generate superior returns, leading to higher investment Qs. Therefore, investment Q increases monotonically with resource quality.

[24] As noted by Rhodes-Kropf and Robinson (2008), a limitation of *SimQ* is that it does not reveal the role of specific types and characteristics of firms' resources in merger matching. To provide further insights, I examine in robustness analyses how similarity in profitability influences merger likelihood and performance, and, in additional analyses, whether acquirer governance quality moderates the relationship between *SimQ* and merger outcomes. Nonetheless, these two tests do not exhaust the possible explanations for when and what firm-pair characteristics drive the observation that firms with similar (or dissimilar) Tobin's Qs merge.

Merger Q arises under the assumption that capital markets at least partially anticipate potential mergers. Under this assumption, a firm's market value incorporates both its stand-alone value and the expected synergy distribution from a potential value-creation merger. From the market's perspective, rational, value-maximizing managers are unlikely to pursue value-destroying mergers, so merger Q arises only when opportunities for value-creating mergers exist. It is defined as the ratio of a firm's expected share of synergy gains to the book value of its assets. The model assumes that, all else equal, higher resource quality enhances both expected synergy and bargaining power in negotiating synergy distribution. Consequently, merger Q also increases with resource quality.

In sum, among firms featured by the same assets, those with higher resource quality exhibit larger pre-merger Tobin's Qs. However, Tobin's Qs are not directly comparable between merging parties featured by different yet complementary asset classes. For instance, a firm producing the highest-quality version of product A may have a higher or lower Q than a firm offering the highest-quality version of product T, depending on how capital markets value the respective products.

To address this limitation, Rhodes-Kropf and Robinson (2008) employ the relative ratio of Tobin's Qs rather than their absolute difference to capture resource quality similarity. Assuming a fixed ratio of valuation multiples between merging firms' asset types, mathematically, firms with closer rankings within their respective asset classes yield larger *SimQ* values, regardless of whether the acquirer has a higher or lower Q compared to the target. For illustration, in a high-Q-acquirer -low-Q-target case: $-|\ln(1/1)| > -|\ln(1/5)| > -|\ln(1/10)|$. In a low-buys-high case: $-|\ln(5/4)| > -|\ln(5/3)| > -|\ln(5/1)|$. Here, the numbers denote resource quality ranks.

Using the negative absolute difference, rather than the signed difference, prevents mechanical misclassification—specifically, the misinterpretation that a low-Q firm acquiring a high-Q firm reflects less similarity than the reverse, regardless of the actual Q-distance (Rhodes-Kropf and Robinson 2008). In summary, a larger *SimQ* reflects greater similarity in the resource quality ranks of merging firms within their respective asset classes.

4.5 Primary Analyses: Interfirm Similarity and Target Selection

To test ***H1a***, ***H2a***, and ***H3a***, I estimate three conditional logit models, specified as Models (1), (2), and (3), respectively, using the pooled sample of the 459 matched groups of actual-control mergers. Each matched group includes the same acquirer paired with different target firms, one being the

actual target and the others serving as controls. These conditional logit models include fixed effects at the matched actual–control group level; however, these fixed effects are not directly estimated. By design, the fixed effects absorb any acquirer- and deal-specific characteristics influencing the likelihood of target selection. The dependent variable (*Deal*) equals one for actual mergers and zero for control observations. Explanatory variables are defined in Appendix A.

$$Deal = \gamma SimPROD + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgRETURN + \beta_4 TrgLEV + \beta_5 TrgINSTOWN + \beta_6 TrgFAGE + GroupFE \quad (1)$$

$$Deal = \gamma GeoProx + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgRETURN + \beta_4 TrgLEV + \beta_5 TrgINSTOWN + \beta_6 TrgFAGE + GroupFE \quad (2)$$

$$Deal = \gamma SimQ + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgQ + \beta_4 TrgRETURN + \beta_5 TrgLEV + \beta_6 TrgINSTOWN + \beta_7 TrgROA + \beta_8 TrgFAGE + GroupFE \quad (3)$$

Next, to test ***H1b***, ***H2b***, and ***H3b***, I re-estimate Models (1) through (3) separately for five subsamples of matched actual-control mergers, categorized by distinct value-creation motives related to operating synergies. These subsamples include mergers aimed at: improving cost efficiency (35 groups, 201 observations); enhancing market position (164 groups, 953 observations); enriching product portfolios (142 groups, 807 observations); expanding into new geographic areas (80 groups, 447 observations); and acquiring innovation resources (38 groups, 211 observations).

Supporting ***H1a*** and ***H1b*** requires the coefficient γ in Model (1) to remain significantly positive across analyses based on the pooled sample and all five subsamples. To support ***H2a*** and ***H2b***, I expect γ in Model (2) to be significantly positive in the pooled sample and in all subsamples except the innovation-driven one, where it is expected to be statistically insignificant. Finally, I anticipate γ in Model (3) to be significantly positive in both the pooled sample and each subsample, consistent with ***H3a*** and ***H3b***.

All continuous variables are winsorized at the 1st and 99th percentiles of the pooled sample to mitigate the influence of outliers. These variables are then standardized by subtracting the mean and dividing by the standard deviation of the corresponding estimation sample in each analysis. The standardization mitigates multicollinearity and facilitates the interpretation of coefficient

estimates and the comparison of coefficients across subgroups. Standard errors are clustered at the matched group level to account for within-group correlation.

The selection of control variables generally follows Chen et al. (2021), which examines the interaction effects of Q similarity and interfirm networks connected by a common lead lender on merger likelihood and performance.[25] The following paragraphs illustrate the rationales for control variable inclusion, focusing on their associations with merger likelihood and interfirm similarity.

I control for the relative size of the target firm to the acquirer (*RelSIZE*), as the relative size of firms correlates with both resource similarity (e.g., Walker and Petty 1978) and merger likelihood (Gorton, Kahl, and Rosen 2009; Alexandridis et al. 2013).[26] *RelSIZE* is measured as the relative market capitalization of merging firms. The target firm's market capitalization reflects the price the acquirer may need to pay to complete the merger. In 420 out of 457 mergers in my sample (with available price premium data), the deal price exceeds the target's market capitalization prior to the merger announcement.[27] Typically, larger firms acquire smaller targets (Gorton et al. 2009). Acquiring a relatively larger firm entails greater value at stake and a higher risk of integration failure (Alexandridis et al. 2013). Consequently, acquirers may hesitate to pursue larger targets but may proceed with more careful due diligence if they do. Accordingly, I expect the coefficient on *RelSIZE* to be negative.

I control for the target firm's asset size (*TrgSIZE*), measured as the natural logarithm of the book value of total assets. Prior studies present mixed evidence on the association between the target firm's asset size and merger likelihood (Bena and Li 2014; Chen et al. 2021). Accordingly, I do not impose a directional expectation for the effect of *TrgSIZE*.

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[25] I do not control for the target firm's Tobin's Q (*TrgQ*) or return on assets (*TrgROA*) in Model (1), which analyzes the effect of product similarity on merger probability. In my sample, *SimPROD* is highly and negatively correlated with *TrgQ* (Spearman $\rho = -0.46$, p-value < 0.01) and *TrgROA* (Spearman $\rho = -0.40$, p-value < 0.01). These significant correlations likely arise because firms' product portfolios influence both Q and ROA (e.g., Selling and Stickney 1989; Waring 1996). Including *TrgQ* and *TrgROA* could therefore bias the coefficient on *SimPROD* (Whited, Swanquist, Shipman, and Moon 2021). I do not include these two variables in Model (2), which analyzes the effect of geographic proximity on merger likelihood, as they are not significantly associated with *GeoProx* and thus do not influence the coefficient estimates of *GeoProx*. Nonetheless, adding the two controls to Models (1) and (2) does not change the sign or statistical significance of the coefficients on *SimPROD* and *GeoProx* reported in Tables 4 and 5.

[26] Chen et al. (2021) do not control for the relative size of merging firms, but they control for the log-transformed book value of total assets and the log-transformed Tobin's Q of both acquirer and target firms. Recall that the fixed effect at the matched actual-control merger group level in the present study absorbs the effects of acquirer firm characteristics, as actual and control mergers involve the actual acquirer. This accounts for different control selections.

[27] The reasons why such transactions occur are beyond the scope of this study. The findings of the present study remain robust after excluding transactions with negative or abnormally high price premiums from the sample (Section 5.6.7).

I also control for the target firm's market-to-book ratio of total assets (*TrgQ*). Rhodes-Kropf and Robinson (2008) propose that firms with higher Tobin's Qs are more likely to engage in mergers due to larger expected gains from a prospective merger, indicating a positive relationship between Q and merger likelihood. Moreover, by construction, *TrgQ* is mechanically associated with Q similarity (*SimQ*). Thus, I control for *TrgQ* in Model (3), which analyzes the effect of *SimQ* on merger probability. However, I do not predict the direction of *TrgQ*'s effect, as Chen et al. (2021) document a negative association between *TrgQ* and the likelihood of a merger.

I control for the target firm's recent stock performance (*TrgRETURN*), measured as the buy-and-hold abnormal returns (BHAR) over the 12 months ending two months before the merger announcement. Prior research shows that overvalued firms tend to acquire undervalued or less overvalued targets (Shleifer and Vishny 2003; Dong et al. 2006; Gu and Lev 2011), indicating a negative association between target firms' recent stock performance and merger likelihood. Dhaliwal et al. (2016) find consistent evidence. Chen et al. (2021) use past-year returns as a matching criterion when selecting control target firms and document an insignificant effect of target firms' recent stock performance on merger probability. Since actual and control targets in this study are matched on the BHAR over the fiscal year before the merger announcement, I expect the coefficient of *TrgRETURN* to be either negative or statistically insignificant.

I also control for target firms' financial performance using return on assets (*TrgROA*). Good performers are less subject to market discipline (Jovanovic and Rousseau 2002) and are less likely to accept takeover bids, particularly when managerial incentives align with maintaining control (Wang and Wu 2020). A firm's financial performance also influences its market valuation and thus *SimQ*. Therefore, I control for *TrgROA* in Model (3) and expect its coefficient to be negative.

I control for target firms' financial leverage (*TrgLEV*), as financially distressed firms are more likely to initiate a sale (Masulis and Simsir 2018; Zha Giedt 2022). Pastena and Ruland (1986) suggest that financially distressed firms with lower financial leverage are more likely to prefer firm sales over bankruptcy, indicating a negative relationship between financial leverage and the likelihood of being acquired. However, other studies document a positive association (Dhaliwal et al. 2016; Chen et al. 2021). Given these mixed findings, I do not impose a directional expectation for the coefficient on *TrgLEV*.

I control for target firms' institutional ownership (*TrgINSTOWN*) to capture governance-related influences on merger likelihood (e.g., Chung and Zhang 2011; Aghion, Van Reenen, and Zingales 2013). Institutional investors may pressure underperforming management to consider firm sales and may advocate for takeovers when seeking value enhancement (e.g., Greenwood and Schor 2009; Burkart and Lee 2022). Consistent with this view, Chen et al. (2021) document a positive association between the target firm's institutional ownership and merger likelihood. Accordingly, I expect the coefficient of *TrgINSTOWN* to be positive.

Finally, I control for the age of the target firm (*TrgFAGE*). While Chen et al. (2021) document a positive association between firm age and merger probability, the underlying mechanism is unclear. Younger firms may attract takeover bids due to promising products or innovation potential. Therefore, I do not have a directional expectation for the effect of *TrgFAGE*.

CHAPTER 5 EMPIRICAL ANALYSES

5.1 Descriptive Statistics

Table 2 presents descriptive statistics for variables used in the primary analyses of acquirers' target selection (Models (1)–(3)) based on a pooled sample of matched actual-control mergers. Panel A presents summary statistics. On average, actual merging firms exhibit greater product similarity and are more likely to be geographically proximate than their matched control counterparts. Actual targets also tend to be younger and have higher institutional ownership. Panel B reports Pearson and Spearman correlation coefficients. The dependent variable, *Deal*, is positively and significantly associated with product similarity, geographic proximity, and the target firm's institutional ownership. Product similarity, geographic proximity, and Q similarity are positively and significantly correlated.

Table 3, Panel A, presents summary statistics for subsamples categorized by value-creation motives. In all five subsamples, actual merging firms exhibit higher product similarity than their matched controls, while Q similarity does not differ significantly between actual and control subgroups. Actual mergers also tend to involve geographically proximate firms, except in the subsample focused on acquiring innovation resources. Panel B reports Pearson correlations within each subsample, which align with the patterns observed in the univariate analyses in Panel A.

5.2 Results of Testing H1a and H1b

Table 4, Panel A, reports coefficient estimates from Model (1), estimated using the pooled sample of operating synergy-driven mergers (column (1)) and five subsamples categorized by value-creation motives related to operating synergies (columns (2)–(6)). In column (1), *SimPROD* is positive and significant (γ = 2.34, t = 15.23), supporting ***H1a***.[28] This suggests that acquirers pursuing operating synergies are more likely to select targets with greater product similarity compared to those with more dissimilar product portfolios. Across all five subsamples, *SimPROD* remains positive and significant at the 1% level (columns (2)–(6)), providing consistent support for ***H1b***.[29] Panel B presents *p*-values from Wald tests evaluating whether *SimPROD* coefficients

[28] Using an alternative linear probit model estimation (non-tabulated), *SimPROD* is also positive and statistically significant at the 1% level (γ = 0.31, t = 24.56), indicating that a one standard deviation increase in product similarity raises the probability of an operating synergy-driven merger by 0.31, an economically significant effect.
[29] The findings remain robust under linear probit model estimates.

differ significantly across subgroups. The results indicate no statistically significant differences, suggesting that product similarity consistently increases merger likelihood regardless of the specific operating synergy motive.

Overall, the results suggest that product similarity increases merger likelihood across various value-creation contexts related to operating synergies. However, the analysis does not distinguish whether the effect is attributable to synergies, lower information asymmetry, or both. Additional analyses, introduced in Section 5.5, aim to disentangle these mechanisms.

Results for control variables generally align with prior literature. *RelSIZE* is negative and significant at the 1% level ($\beta_1 = -0.50$, $t = -3.93$), indicating that acquirers are less likely to select relatively larger targets, particularly in mergers aimed at enhancing market position. *TrgSIZE* is positive and significant ($\beta_2 = 0.50$, $t = 1.72$), indicating acquirers' preferences for targets with a higher book value of assets, particularly in the pursuit of improving cost efficiency. *TrgINSTOWN* is positive and significant ($\beta_5 = 0.60$, $t = 5.51$), consistent with the idea that institutional ownership facilitates firm sales. This effect, however, is insignificant in mergers focused on geographic expansion and innovation. Other control variables are statistically insignificant. Notably, while the pooled sample shows an insignificant effect for *TrgFAGE*, subsample analyses reveal a negative and significant coefficient in product-enrichment mergers ($\beta_6 = -0.25$, $t = -2.07$) and a positive and significant coefficient in geographic expansion mergers ($\beta_6 = 0.41$, $t = 2.67$). Additionally, *TrgRETURN* is significantly positive ($\beta_3 = 0.29$, $t = 1.89$) in the subsample motivated by geographic expansion, consistent with Kaul and Wu (2016), who find that acquirers prefer well-performing targets when entering new geographic markets.

5.3 Results of Testing H2a and H2b

Table 5, Panel A, presents coefficient estimates from Model (2), using the pooled sample of operating synergy-driven mergers (column (1)) and five value-creation-based subsamples (columns (2)–(6)). In column (1), *GeoProx* is positive and significant ($\gamma = 0.78$, $t = 11.61$), supporting ***H2a***.[30] This suggests a greater likelihood of selecting geographically proximate targets over distant alternatives in mergers driven by operating synergies.

[30] Based on estimates from an alternative linear probit model (non-tabulated), *GeoProx* is positive and significant at the 1% level ($\gamma = 0.15$, $t = 14.60$), suggesting that a one standard deviation increase in geographic proximity is

Across subsamples, *GeoProx* remains positive and significant at the 1% level, except in innovation-driven mergers, supporting ***H2b***.[31] Panel B reports tests of whether the coefficients on *GeoProx* differ significantly across subsamples. The positive effect is strongest in geographic expansion mergers ($\gamma = 1.47$, $t = 5.04$), weakest in product-enrichment mergers ($\gamma = 0.48$, $t = 4.92$), and insignificant in innovation-oriented mergers ($\gamma = 0.20$, $t = 0.95$). These findings are consistent with the expected synergy implications of geographic proximity under varying value-creation motives.

Control variable results generally corroborate prior expectations. *RelSIZE* is negative and significant ($\beta_1 = -0.41$, $t = -4.00$), while *TrgSIZE* ($\beta_2 = 0.83$, $t = 3.67$) and *TrgINSTOWN* ($\beta_5 = 0.65$, $t = 6.86$) are positive and significant. *TrgFAGE* is negative and significant ($\beta_6 = -0.14$, $t = -2.31$) based on the pooled sample estimates. Subsample analyses show that the negative effect of target firm age is concentrated in mergers seeking product or innovation resources, whereas geographic expansion mergers are more likely to involve older targets. The remaining control variables are statistically insignificant. Still, an exception is that *TrgRETURN* is positive and significant ($\beta_3 = 0.40$, $t = 1.97$) in geographic expansion mergers.

5.4 Results of Testing H3a and H3b

Table 6, Panel A, presents coefficient estimates from Model (3), using the pooled sample of operating synergy-driven mergers (column (1)) and five subsamples categorized by value-creation motives (columns (2)–(6)). In the pooled sample, the coefficient for *SimQ* is positive and significant ($\gamma = 0.22$, $t = 2.99$), supporting ***H3a***.[32] This result indicates that acquirers in operating synergy-driven mergers are more likely to select target firms with similar resource quality ranks, as measured by similarity in the log-transformed Tobin's Q.

The coefficients on *SimQ* are also positive and significant in subsamples focused on enhancing market position ($\gamma = 0.18$, $t = 1.68$), enriching product portfolios ($\gamma = 0.29$, $t = 2.52$),

associated with an increase of 0.15 in the probability of an operating-synergy-driven merger, an economically significant effect.

[31] The findings remain robust under linear probit model estimates.

[32] Using an alternative linear probit model estimation (non-tabulated), *SimQ* remains positive and statistically significant at the 1% level ($\gamma = 0.03$, $t = 2.69$), suggesting that a one standard deviation increase in resource quality similarity raises the probability of an operating synergy-driven merger by 0.03, an economically smaller effect compared to those of the other two similarity dimensions. Nonetheless, an increase of 0.03 in merger probability is still economically meaningful, considering that the annual delisting rate of public firms due to M&As is approximately 9%.

and acquiring innovation resources (γ = 0.56, t = 2.10). However, *SimQ* is not significant in mergers cost-efficiency-driven mergers (γ = 0.22, t = 0.67) or geographic expansion mergers (γ = –0.01, t = –0.06). The findings reject ***H3b***.[33] Panel B suggests that the effect of *SimQ* on acquirers' target selection generally does not significantly differ across different value-creation motives. Panel B tests whether *SimQ* coefficients differ significantly across subgroups. In general, the differences are not statistically significant, with one exception: the difference between geographic expansion and innovation-driven mergers is significant at the 10% level. One possible explanation is that geographic location may not strongly correlate with Tobin's Q, while innovation resources, central to innovation-focused mergers, may exert a substantial influence on this metric.

Overall, the results suggest that Q similarity increases merger likelihood in selected contexts, particularly when strategic complementarities in intangible assets (e.g., growth prospects) are present.

For the two control variables included in Model (3) but not in Models (1) and (2), *TrgQ* is positive and statistically significant at the 1% level (β_3 = 0.38, t = 4.41), particularly in mergers focused on product enrichment and innovation. *TrgROA* is statistically insignificant in the pooled sample. It is significantly positive (β_7 = 0.20, t = 1.72) in mergers focused on enriching product portfolios, indicating that acquirers prefer profitable targets when pursuing product enrichment. The coefficients on *TrgROA* in subsamples motivated by cost efficiency and innovation resources are significantly negative, as expected. The results of other control variables are broadly consistent with those reported in Tables 4 and 5.

5.5 Additional Analyses

Sections 5.5.1 and 5.5.2 evaluate shareholder wealth outcomes and long-term merger performance. If acquirers act to maximize shareholder value, then all three similarity measures are expected to positively correlate with acquirer shareholder wealth outcomes and long-term merger performance.

The observed positive effects of product similarity and geographic proximity on merger likelihood may arise from either the synergy motive, reduced information asymmetry, or a combination of both. Sections 5.5.3 and 5.5.4 explore these underlying mechanisms.

[33] When estimating linear probit models, *SimQ* is significantly positive only in the subsample categorized by the motive of enriching product portfolios, consistently rejecting ***H3b***.

A positive association between Q similarity and merger likelihood is expected if firms face low search frictions in identifying potential merger partners for operating synergies. Section 5.5.5 empirically validates the low search friction assumption. Section 5.5.6 examines why Q similarity positively influences merger likelihood in certain value-creation contexts but not in others, focusing on the substitutability of target resources (or heterogeneity in the quality of potential targets' resources).

Section 5.5.7 examines the effect of acquirer entrenchment on the relationships between the three dimensions of interfirm similarity and merger outcomes. Despite disclosed synergy motives, managerial entrenchment incentives could have driven mergers and influenced negotiations.

5.5.1 Shareholder wealth effects

Shareholder wealth effects in operating synergy-driven mergers

If acquirers select targets based on expected net gains from mergers, thereby driving the observed positive associations between three interfirm similarity proxies and merger likelihood, then interfirm similarity should also correlate positively with acquirer shareholder wealth outcomes around the merger announcement. To assess these outcomes, I employ two measures: the acquirer's cumulative abnormal percentage returns (*ACAR*) and dollar gains (*AGAIN*) (e.g., Chen et al. 2021).

To provide further insights, I examine the relationship between interfirm similarity and the expected synergy value from the merger (*CGAIN*) (e.g., Bradley, Desai, and Kim 1988), as well as the distribution of synergy between the merging firms. The acquirer's share of synergy depends on its bargaining power relative to the target. I capture this distribution using a proxy for the target's relative bargaining power (*RELTGAIN*) (Ahern 2012), along with the target's CARs (*TCAR*) and dollar gains (*TGAIN*). Computation details are provided in Appendix A.

From the initial sample of 459 mergers used in the target selection analyses, I exclude two deals due to missing wealth effect data, four involving multiple same-day announcements by the acquirer, and one hostile takeover. These exclusions yield a final sample of 452 mergers for examining shareholder wealth effects. Using hand-collected data, I update the SDC database merger announcement dates to reflect the date the firms publicly announced a definitive merger

agreement. Figure 1 presents box plots of *CGAIN*, *AGAIN*, and *ACAR* across five value-creation motives related to operating synergies.

To assess the effect of each similarity dimension on shareholder wealth outcomes, I estimate the following OLS regression model (Model (4)) with acquirer industry and announcement year fixed effects, using the sample of 452 mergers. The dependent variable (*DV*) is one of six measures capturing shareholder wealth effects. *Similarity* refers to *SimPROD*, *GeoProx*, or *SimQ* in separate regressions. Standard errors are two-way clustered by acquirer industry and merger announcement year. Other variables are defined in Appendix A.

$$\begin{aligned} DV = {} & \alpha + \gamma Similarity + \beta_1 Cash + \beta_2 Stock + \beta_3 Compete + \beta_4 Toehold + \beta_5 Tender + \beta_6 RelDealSize \\ & + \beta_7 AcqME + \beta_8 AcqRETURN + \beta_9 AcqLEV + \beta_{10} AccqINSTOWN + \beta_{11} AcqFAGE \\ & + \beta_{12} TrgME + \beta_{13} TrgRETURN + \beta_{14} TrgLEV + \beta_{15} TrgINSTOWN + \beta_{16} TrgFAGE \\ & + AcqIndFE + YearFE + \varepsilon \end{aligned} \tag{4}$$

Table 7, Panel A, presents summary statistics and Pearson correlations among variables. Panel B presents coefficient estimates from Model (4). *SimPROD* is significantly and positively associated with *AGAIN* ($\gamma = 0.07$, $t = 1.85$) and *ACAR* ($\gamma = 0.18$, $t = 5.02$), and significantly and negatively associated with *RELTGAIN* ($\gamma = –0.13$, $t = –2.00$). These results suggest that acquirers experience more favorable shareholder reactions in mergers with greater product similarity, supporting the interpretation that product similarity increases merger likelihood due to expected synergy gains. *GeoProx* is not significant across all model specifications, indicating that geographic proximity does not significantly affect expected merger gains or losses for either party. *SimQ* is significantly and positively associated with *CGAIN* ($\gamma = 0.08$, $t = 2.16$) and *AGAIN* ($\gamma = 0.09$, $t = 2.05$), suggesting that mergers between firms with more similar resource quality yield greater expected synergies and higher NPV of the acquirer's expected gains.

Fich et al. (2018) recommend considering the potential influence of mergers with substantial acquirer gains or losses when examining shareholder wealth outcomes. Following Moeller, Schlingemann, and Stulz (2005) and Fich et al. (2018), I define deals with substantial acquirer gains or losses as those with absolute *AGAIN* values greater than or equal to $500 million or $1 billion. Among the 452 mergers, 110 involve absolute *AGAIN* values of $500 million or more, and 74 of $1 billion or more. To determine whether such deals drive the observed relationships, I re-estimate the models excluding these observations. As shown in Table 7, Panel B, when the

sample is restricted to mergers with absolute *AGAIN* values below $500 million, only the positive association between *SimPROD* and *ACAR* remains statistically significant. The loss of significance in other coefficients suggests that large-gain or large-loss deals have likely driven the originally observed relationships, aligning with Fich et al.'s (2018) recommendation.

Shareholder wealth effects across value-creation motives

To assess whether the associations between three dimensions of interfirm similarity and shareholder wealth outcomes differ across value-creation motives, I estimate the following OLS regression model, Model (5), specified as follows.

$$\begin{aligned} DV = \alpha + (&\gamma Similarity + \beta_1 Cash + \beta_2 Stock + \beta_3 Compete + \beta_4 Toehold + \beta_5 Tender \\ &+ \beta_6 RelDealSize + \beta_7 AcqME + \beta_8 AcqRETURN + \beta_9 AcqLEV + \beta_{10} AccqINSTOWN \\ &+ \beta_{11} AcqFAGE + \beta_{12} TrgME + \beta_{13} TrgRETURN + \beta_{14} TrgLEV + \beta_{15} TrgINSTOWN \\ &+ \beta_{16} TrgFAGE) \times MotiveG + AcqIndFE + YearFE + \varepsilon \end{aligned} \tag{5}$$

Table 8, Panel A, presents summary statistics for the dependent variables and their Pearson correlation coefficients with the three interfirm similarity proxies across value-creation subgroups. Panel B reports coefficient estimates from Model (5) using the 452 mergers. Panel C displays only statistically significant coefficient estimates for interfirm similarity proxies within specific value-creation motives. Statistical significance is determined based on *p*-values from Wald tests of linear combinations of the baseline subgroup coefficient and the corresponding interaction term.

SimPROD is significantly and positively associated with *CGAIN* ($\gamma = 0.40$, *p*-value = 0.027), *AGAIN* ($\gamma = 0.48$, *p*-value = 0.039), and *ACAR* ($\gamma = 0.34$, *p*-value = 0.060) in cost-efficiency-driven mergers, indicating that product similarity enhances both synergy creation and acquirer negotiation power in such deals. In contrast, in innovation-driven mergers, *SimPROD* is significantly and negatively associated with *CGAIN* ($\gamma = -0.90$, *p*-value = 0.080) and *TGAIN* ($\gamma = -0.77$, *p*-value = 0.041), but not significantly associated with acquirer wealth outcomes. Additionally, *SimPROD* is negatively associated with target shareholder negotiation outcomes in mergers aimed at enhancing market position (*RELTGAIN*, $\gamma = -0.29$, *p*-value = 0.080) and geographic expansion (*TCAR*, $\gamma = -0.31$, *p*-value = 0.010). It has no significant effect on mergers aimed at enriching product portfolios.

GeoProx remains statistically insignificant across all synergy motive subgroups, reinforcing earlier findings that the capital market does not consider geographic proximity as materially influencing merger gains or losses.

SimQ is significantly and positively associated with *CGAIN* ($\gamma = 0.30$, p-value = 0.068) and *AGAIN* ($\gamma = 0.21$, p-value = 0.062) in mergers aimed at enriching product portfolios. The findings support the interpretation that, when pursuing scarce resources, acquirers select target firms with more similar Tobin's Qs because they anticipate larger net gains from the distribution of synergies in such mergers, supporting positive assortative matching. In innovation-driven mergers, *SimQ* is positively associated with *ACAR* ($\gamma = 0.21$, p-value = 0.071) while negatively associated with *RELTGAIN* ($\gamma = -0.26$, p-value = 0.020) and *TGAIN* ($\gamma = -0.36$, p-value = 0.044). The results are consistent with the interpretation that acquirers balance negotiation power and synergy potential when choosing targets with similar Tobin's Qs.

5.5.2 Long-run merger performance

This subsection revisits the research question originally posed by Harrison et al. (1991)—whether interfirm similarity influences long-run merger performance—using a different sample (setting) and research design. Suppose acquirers systematically prefer targets with greater similarity due to anticipated economic benefits, and these expected gains are realized post-merger. In that case, mergers between more similar firms should exhibit superior long-run merger performance, consistent with patterns observed in target selection.

Long-run merger performance is measured by the change in industry-adjusted ROA (ΔROA) from two years before to two years after the merger ($\Delta ROA[-2,+2]$).[34] Industry-adjusted ROA is computed by subtracting the arithmetic mean ROA of all firms in the same industry-year from each firm's ROA. For pre-merger years, I calculate a weighted average ROA for the acquirer and target, weights determined by the book value of total assets at the corresponding fiscal year-end. I also consider two alternative measurement windows: (i) the merged firm's ROA in the first fiscal

[34] The two-year post-merger observation period is determined based on three considerations. First, Chartier et al. (2018) report that merged firms typically realize full cost synergies and approximately 60% of revenue synergies by the end of the second year after deal completion. Second, while the expected economic benefits may not fully materialize within two years, extending the observation window risks introducing additional noise into the merger performance measure, such as the impact of another merger. Third, limiting the window to two years helps preserve the sample size, as extending the post-merger observation period reduces the number of mergers with available data on post-merger performance.

year following merger completion minus the pre-announcement weighted average ROA ($\Delta ROA[-1,+1]$); and (ii) the ROA in the second fiscal year after merger completion minus the pre-announcement weighted average ROA ($\Delta ROA[-1,+2]$).

I estimate the following OLS regression model (Model (6)) to examine whether interfirm similarity proxies are associated with long-run merger performance. The dependent variable is one of the three ΔROA measures.[35]

$$DV = \alpha + \gamma Similarity + \beta_1 AcqSIZE + \beta_2 AcqRETURN + \beta_3 AcqLEV + \beta_4 AccqINSTOWN + \beta_5 AcqFAGE + \beta_6 TrgSIZE + \beta_7 TrgRETURN + \beta_8 TrgLEV + \beta_9 TrgINSTOWN + \beta_{10} TrgFAGE + AcqIndFE + YearFE + \varepsilon \quad (6)$$

Table 9, Panel A, presents univariate comparisons of ΔROA across mergers classified by high versus low interfirm similarity, using the pooled sample with available data. The results indicate that mergers with greater product similarity and more closely aligned Tobin's Qs tend to exhibit stronger long-run financial performance. Panel B reports coefficient estimates from multivariate OLS regressions. In contrast to the univariate findings, none of the interfirm similarity proxies—product similarity, geographic proximity, or Q similarity—are significantly associated with long-run ΔROA.[36] These results are robust to alternative long-run performance measures using industry-median-adjusted ROA.

5.5.3 Synergy mechanism: Interactive effect of product similarity and geographic proximity

From a synergy perspective, product similarity and geographic proximity may jointly enhance a merged firm's market position and facilitate post-merger integration. DeLong (2001) provides empirical support for this interaction in bank mergers. Similarly, Almazan et al. (2010) find that

[35] I exclude control variables for deal characteristics, as prior studies suggest they do not significantly influence long-run merger performance (e.g., Cai and Sevilir 2012). In addition, compared to Model (4), I use asset size rather than market capitalization to control for firm size, as the dependent variables in this analysis—based on return on assets (ROA)—are more closely related to book values of total assets.

[36] Nonetheless, interpreting the results of the long-run performance analysis requires consideration of two key limitations. First, changes from the pre-merger weighted average ROA to post-merger ROA may not accurately capture performance attributable to the merger. For instance, some related mergers involve partial asset sales (Maksimovic, Phillips, and Prabhala 2011), prompting some studies to measure performance from the merger completion year onward. Second, the OLS regression analysis is subject to survivorship bias, as mergers excluded due to missing post-merger data may represent failed deals. While survival analysis using an indicator for post-merger performance improvement could address this concern, defining and identifying long-term merger failures is outside the scope of this study and is therefore not discussed further.

regions with a high concentration of product-market peers tend to encourage horizontal mergers, attributing this to resource sharing, labor market pooling, and knowledge spillovers.

However, this positive interactive effect is less likely to materialize, if not absent, in mergers focused on enriching product portfolios or expanding geographically, where dissimilarity in product or geographic markets may be strategically beneficial, such as cross-selling opportunities. No interaction is expected in innovation-driven mergers, as Section 5.3 shows that geographic proximity does not affect the likelihood of such mergers.

In summary, I expect a significantly positive interactive effect of product similarity and geographic proximity on the likelihood of mergers aimed at improving cost efficiency and enhancing market position. I estimate the following linear probit model with fixed effects at the matched actual-control merger group level to test the prediction.

$$Deal = \alpha + \gamma_1 SimPROD + \gamma_2 GeoProx + \gamma_3 SimPROD \times GeoProx + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgRETURN + \beta_4 TrgLEV + \beta_5 TrgINSTOWN + \beta_6 TrgFAGE + GroupFE + \varepsilon \quad (7)$$

Table 10 presents coefficient estimates from Model (7). The interaction term is positive and significant in the pooled sample ($\gamma_3 = 0.07$, $t = 7.14$) and in subsamples motivated by improving cost efficiency ($\gamma_3 = 0.08$, $t = 3.02$) and enhancing market position ($\gamma_3 = 0.09$, $t = 6.85$). It is statistically insignificant in the remaining subsamples. These results are consistent with the synergy-based expectations across synergy motive contexts, supporting the synergy mechanism underlying the positive impact of product similarity and geographic proximity on merger likelihood.

5.5.4 Information mechanism: The role of target firms' information accessibility

An alternative explanation for the observed positive effects of product similarity (*SimPROD*) and geographic proximity (*GeoProx*) on merger likelihood is that both serve as proxies for reduced information asymmetry between firms. Product similarity may reflect a status of low information asymmetry, as product-market peers have evaluated one another through ongoing industry interactions. Geographic proximity may function as an information channel that lowers information asymmetry.

This subsection examines whether the positive effects of *SimPROD* and *GeoProx* on merger likelihood can be attributed, at least in part, to reduced information asymmetry through two tests. First, I examine whether including direct proxies for information asymmetry reduces the magnitude or significance of the *SimPROD* and *GeoProx* coefficients. If these variables mainly reflect reduced information asymmetry, their effects should diminish or vanish when such controls are included. If synergy considerations remain the dominant factor, their effects should persist. Additionally, the direct information asymmetry control should itself be statistically significant under the information asymmetry-based explanation.

Second, I test whether proxies for information asymmetry moderate the effects of *SimPROD* and *GeoProx* on the likelihood of mergers. According to Haunschild and Beckman (1998), firms may rely on alternative, potentially substitutive or complementary, information sources in making merger decisions. If information asymmetry is the underlying mechanism behind *SimPROD* and *GeoProx*, significant interaction effects with these alternative proxies are expected.

Effects of the opaqueness of potential target firms' publicly available information

To assess the opaqueness of potential target firms' publicly available information, I employ two alternative measures: the absolute value of performance-matched abnormal discretionary accruals (*DACC*) (Karpoff, Lee, and Masulis 2013) and stock return non-synchronicity (*NonSynchronicity*) (Martin and Shalev 2017).[37] A higher absolute value of abnormal accruals indicates lower financial reporting quality, reflecting greater information opaqueness. Conversely, higher stock return non-synchronicity implies greater incorporation of firm-specific information into stock prices, indicating lower opaqueness. In other words, *DACC* captures whether a firm's information is opaque, whereas *NonSynchronicity* indicates the amount of firm-specific information available.

[37] Chen et al. (2021) construct a composite measure of information asymmetry using principal component analysis (PCA) of seven proxies: analyst coverage, firm age, firm size, asset tangibility, idiosyncratic return volatility, bid-ask spread, and abnormal accruals. For this study's sample, the Kaiser-Meyer-Olkin (KMO) test yields a value of 0.567, which does not support the adequacy of this approach. Furthermore, two of the seven proxies are already included as control variables in Models (1) and (2), and the PCA yields two components with eigenvalues larger than one. This method is therefore deemed implausible for use here and would complicate interpretation. Nonetheless, untabulated robustness checks indicate that controlling for the two principal components does not alter the sign or significance of the interfirm similarity measures in the pooled sample of operating synergy-driven mergers.

However, the opaqueness of target firms' publicly available information may not exert a significant effect in this setting. Several studies indicate that, in same-industry mergers, acquirers may not rely heavily on publicly available information when evaluating potential targets at the time of making merger decisions (Raman et al. 2013; Martin and Shalev 2017; Perafán-Peña et al. 2022). Instead, they may draw on industry expertise and private communications to more accurately assess a target's fundamentals and merger prospects. As a result, the quality and quantity of publicly available information about potential target firms may not influence the likelihood of mergers aimed at operating synergies.

Requiring non-missing values for *DACC* reduces the sample size to 447 matched groups of actual-control mergers (2,528 observations) for the *DACC*-based analysis, and to 408 matched groups (2,245 observations) for the *NonSynchronicity*-based analysis. To address concerns that *SimPROD* and *GeoProx* may primarily proxy for low information asymmetry, I first augment the conditional logit models (Models (1) and (2)) with a control variable representing the opaqueness of target firms' publicly available information (*DACC* or *NonSynchronicity*). Next, to examine potential moderating effects, I estimate a linear probit model with fixed effects at the matched actual-control merger group level, specified as follows. In this specification, *Similarity* denotes either *SimPROD* or *GeoProx*, and *TrgInfo* refers to either *DACC* or *NonSynchronicity*.

$$Deal = \alpha + \gamma_1 Similaity + \gamma_2 TrgInfo + \gamma_3 Similarity \times TrgInfo + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgRETURN + \beta_4 TrgLEV + \beta_5 TrgINSTOWN + \beta_6 TrgFAGE + GroupFE + \varepsilon \quad (8)$$

Table 11 presents coefficient estimates from the multivariate regression analyses. The coefficients for *SimPROD* and *GeoProx* remain robust after controlling for the two alternative measures of information asymmetry. These results indicate that the positive effects of product similarity and geographic proximity on merger likelihood cannot be fully attributed to acquirers' preferences for low information asymmetry.

The coefficients on the two information opaqueness measures and their interaction terms with product similarity are not statistically significant. This finding suggests that the opaqueness of publicly available information about potential targets neither influences the likelihood of operating synergy-driven mergers nor moderates the effect of product similarity on merger likelihood.

In contrast, the interaction between geographic proximity and target firms' abnormal accruals is significantly negative ($\gamma_3 = -0.05$, $t = -4.43$), indicating that acquirers are less likely to select geographically proximate targets with high levels of earnings management. This result aligns with and complements the finding of Perafán-Peña et al. (2022), who suggest that acquirers discount peers with high abnormal accruals when negotiating merger prices.

Similarly, the interaction between geographic proximity and the amount of target firm-specific information is significantly negative ($\gamma_3 = -0.03$, $t = -2.91$). This suggests that greater availability of firm-specific information in the stock market diminishes the positive effect of geographic proximity on the likelihood of mergers aimed at operating synergies. This finding is consistent with prior findings that alternative information sources can weaken the information advantage conferred by geographic proximity or enable acquirers to identify investment opportunities beyond their immediate geographic vicinity (Schildt and Laamanen 2006; Ragozzino and Reuer 2011; Bick et al. 2017).

Effects of alternative pairwise channels for private information

This subsection examines whether alternative channels for private information exchange between firms influence merger likelihood and whether these channels moderate the effects of product similarity and geographic proximity on merger probability.

Building on prior research, I employ two indicators to capture alternative channels that may reduce information asymmetry in M&A settings: closely connected boards (*D1stConn*) (Ishii and Xuan 2014; Cai and Sevilir 2012) and a common auditor (*CAudit*) (Dhaliwal et al. 2016). *D1stConn* is a binary variable equal to one if at least two directors from the boards of the merging firms either obtained the same bachelor's degree (or higher) from the same institution within one year or worked at the same third company for more than 365 days as of the beginning of the fiscal year preceding the merger announcement; it equals zero otherwise. *CAudit* is an indicator equal to one if the same auditor issued audit opinions for both firms in the fiscal year prior to the merger announcement, and zero otherwise.

I first estimate the adjusted conditional logit models (Models (1) and (2)), including a control for *D1stConn* or *CAudt*, to assess whether the positive effects of *SimPROD* and *GeoProx* persist after accounting for these alternative private information channels. I then estimate linear probit models (Model (8)) to examine whether these pairwise information channels moderate the

effects of *SimPROD* and *GeoProx* on merger likelihood. In these models, *Similarity* refers to either *SimPROD* or *GeoProx*, and *TrgInfo* refers to either *D1stConn* or *CAudit*. I interpret a positive (negative) interaction effect as evidence that the private information channel complements (substitutes for) the effect of product similarity or geographic proximity.

Table 12 presents the coefficient estimates. The coefficients for *SimPROD* and *GeoProx* remain statistically significant after controlling for *D1stConn* and *CAudit*, consistently indicating that the effects of *SimPROD* and *GeoProx* cannot be attributed solely to them serving as proxies for reduced information asymmetry.

The interactions between *SimPROD* and *D1stConn* (γ_3 = 0.09, t = 2.16) and between *SimPROD* and *CAudit* (γ_3 = 0.07, t = 3.25) are significantly positive, suggesting that the presence of either alternative information channel enhances the positive effect of *SimPROD* on the likelihood of operating synergy-driven mergers. In contrast, the interaction between *GeoProx* and *D1stConn* is significantly negative (γ_3 = –0.09, t = –3.12), while the interaction between *GeoProx* and *CAudit* is not statistically significant (γ_3 = –0.02, t = –0.98). These results imply that closely connected boards may substitute for the informational benefits of geographic proximity, enabling acquirers to consider target firms beyond their immediate geographic areas. Notably, *CAudit* does not exhibit a significant main effect on the likelihood of operating synergy-driven mergers.

These patterns suggest that closely connected boards may serve as an alternative, substitutive channel for geographic proximity in reducing information asymmetry. However, for product-market peers pursuing mergers for operating synergies, such private information channels are likely endogenously established to facilitate information exchange before eventual deal execution. Therefore, the positive interaction effects between *SimPROD* and both *D1stConn* and *CAudit* should be interpreted cautiously. It is plausible that the synergies associated with product similarity incentivize firms to create or strengthen private information channels before deal execution.

In sum, the results yield two primary implications. First, the evidence suggests that the information asymmetry mechanism is unlikely to be the primary driver of the positive relationship between product similarity and merger likelihood. Although information asymmetry plays a role in the relationship between geographic proximity and merger likelihood, it does not fully account for the observed effects. Second, while the quality and quantity of publicly available information

about target firms do not appear to significantly influence the likelihood of operating synergy-driven mergers, the presence of certain private information channels does.

5.5.5 Validation of the low search friction assumption

In developing ***H3a***, I posit that search frictions in the context of operating synergy-driven mergers are generally low. To test this assumption, I estimate the linear probit model (Model (8)) with *Similarity* denoting *SimQ* and *TrgInfo* referring to one of four proxies for information asymmetry: *DACC*, *NonSynchronicity*, *D1stConn*, or *CAudit*. Under the low search friction assumption, I do not expect these proxies to moderate the relationship between *SimQ* and merger likelihood. Table 13 presents the coefficient estimates. *SimQ* remains significantly positive, and its interactions with each of the four *TrgInfo* proxies are statistically insignificant. These findings suggest that the accessibility to potential target firms' information does not affect the relationship between *SimQ* and merger likelihood. The findings support the assumption that U.S. public firms in related industries generally face low search frictions when pursuing mergers for operating synergies.

5.5.6 Moderating effect of the substitutability of target resources

The results from testing ***H3b*** show that the positive relationship between Q similarity and merger likelihood is statistically significant only in mergers motivated by enhancing market position, enriching product portfolios, and acquiring innovation resources. Among these, only in mergers aimed at enriching product portfolios does the relationship remain robust under an alternative model specification that omits the control for target firms' Tobin's Q (see Section 5.6.4) and under an alternative estimation approach using a linear probit model (non-tabulated). To provide a possible explanation for the variation, this subsection examines whether the substitutability of target resources moderates the strength of the positive relationship between Q similarity and merger likelihood. This test is informed by a necessary but previously unexamined element in the theory developed by Rhodes-Kropf and Robinson (2008): that the complementary resources driving the merger are scarce.

Beyond low search frictions, another necessary condition for this observed positive relationship between Q similarity and merger likelihood is the scarcity—and thus low substitutability—of the resources sought by acquirers. As previously discussed, the positive assortative matching stems from acquirers weighing the greater synergy potential of integrating

high-quality targets against the reduced bargaining power in negotiating with such targets. When substitutability is low, resource quality among potential targets is more heterogeneous. This heterogeneity enhances the value of assortative matching, as it increases the likelihood that merging with a target whose resource quality closely aligns with that of the acquirer yields different value implications than merging with a less similar target (Lentz and Mortensen 2010).

I expect the positive effect of resource quality similarity on merger likelihood to be strongest when resource substitutability is moderately low and weaker when substitutability is either very high or very low. When substitutability is very high, as in the case of standardized products, differences in resource quality might be negligible; therefore, acquirers may be indifferent to differences in resource quality. In such scenarios, the tradeoff between synergy potential and bargaining power becomes less relevant, and other factors, such as the target firm's inclination to sell due to liquidity needs, may play a greater role in target selection. Furthermore, transacting in the arm's length market might be a better strategy to access those standardized resources than acquisitions. Additionally, high substitutability may constrain the variation in *SimQ* within these matched groups of actual-control mergers, reducing the statistical power to detect its effect.

Conversely, when substitutability is very low, acquirers may face a lack of viable alternatives, limiting their discretion in target selection.[38] The research design choice and data requirement of one-to-five control targets may exclude these mergers from the primary sample. For example, *AbbVie Inc.*'s $21 billion acquisition of *Pharmacyclics* in 2015 was driven by the unique value of its cancer treatment drug, Imbruvica. Although *AbbVie* was developing a competing drug, it found that the two could complement each other. Given the unique fit of *Pharmacyclics'* resources, no viable alternatives existed, leaving *AbbVie* with limited bargaining leverage. The offer price was later questioned as excessively high (Merced and Pollack 2015), suggesting that *AbbVie* may have captured a relatively small share of the expected synergy.

Ahern (2012) defines an industry's product resources as exhibiting low substitutability based on either of the following three conditions: (1) high industry-level profitability, measured by the ratio of value-added to total industry output from the BEA USE table; (2) high standard

[38] In such cases, I speculate that the competition among potential acquirers plays a more influential role in shaping merger matching outcomes. Future research may shed relevant insights into this.

deviation of firms' profit margins within the industry; and (3) a high industry concentration ratio. Higher profit margins indicate resource scarcity, aligning with lower substitutability. Greater within-industry dispersion in firm-level profit margins implies increased heterogeneity in resource quality, consistent with lower substitutability. A high concentration ratio indicates product-market dominance by a few firms, a pattern typically associated with high product differentiation (e.g., Shaked and Sutton 1987), implying low substitutability. I calculate these three measures by IO industry: industry-level profit margin (*ioindPM*), standard deviation of firm profit margins within the industry (*ioindPMSD*), and industry concentration ratio using Compustat sales data (*ioindHHI*).[39] Low resource substitutability implies high resource quality heterogeneity.

To benchmark sample target industries against the broader economy, I classify all IO industries, excluding government sectors, into high and low substitutability groups for each measure using annual median splits, yielding six groups across all industries each year. Table 14, Panel A, categorizes the 459 sample mergers into these six groups based on the target firms' industry classification in the year before the merger announcement. Most mergers occur in industry-years characterized by high profit margins (317 out of 459), high profit margin heterogeneity (402 out of 459), and low concentration ratios (408 out of 459). These patterns suggest that firms in more profitable, more differentiated, and less concentrated industries are more likely to be selected as targets in operating synergy-driven mergers. In other words, in the majority of sample mergers, target resources exhibit low substitutability relative to the broader economy.

To examine whether target resource substitutability (i.e., heterogeneity in resource quality among potential targets) moderates the relationship between Q similarity and merger likelihood, I estimate a linear probit model. This model extends Model (3) by including an interaction term between *SimQ* and an indicator for resource quality heterogeneity. To capture varying levels of heterogeneity, I construct two indicators: *HIGH*, equal to one if the proxy exceeds the sample

[39] I use the industry concentration ratio to capture the substitutability of resources among potential target firms. Since this study examines mergers between U.S. public firms and does not consider private firms as potential target firms, concerns about the exclusion of private firms in measuring industry concentration ratios based on Compustat sales data (Ali, Klasa, and Yeung 2009) do not apply. Moreover, the exclusion of private targets is justified by Capron and Shen (2007), who argue that acquirers endogenously choose between public and private targets based on merger type and perceived information asymmetry. Their findings also suggest that acquirers purchasing public targets would have fared worse had they acquired private targets instead.

median (high level) and zero otherwise (low level); and *MOD*, equal to one if the proxy falls within the middle three quintiles of the sample distribution (moderate level) and zero otherwise (tails).

Table 14, Panel B, presents the coefficient estimates. *SimQ* is positive and statistically significant (based on a one-tailed test) when the target industry-level profit margin is high or moderate, when profit margin heterogeneity is high or in the tails of the sample distribution, and when the industry concentration ratio is high or in the tails.[40] These results support the view that the positive relationship between Q similarity and merger likelihood is stronger when target resource substitutability is low; that is, when target candidates possessing the desired resources are more heterogeneous.[41]

It is important to recall that scenarios involving extremely low substitutability (e.g., unique resources) may not be fully captured by the research design employed here (i.e., the use of matched control firms and IO-based substitutability measures). Likewise, mergers are less likely when target resources exhibit extremely high substitutability (e.g., standardized products). Thus, when interpreting the findings of this subsection, particularly in conjunction with the subgroup analyses by merger motive, readers should keep in mind dimensions of resource substitutability not fully reflected in the three industry-level proxies.

In conclusion, this subsection provides empirical support for the role of target resource substitutability in explaining the varying strength of the positive relationship between Q similarity and merger likelihood across merger motive contexts.

5.5.7 Effect of acquirer entrenchment

This study uses acquirers' merger disclosures to identify transactions motivated by operating synergies. However, acquirer disclosures may not faithfully disclose the presence of any value-destroying motivations behind merger decisions. Although agency problems are less likely in related mergers (Anand and Singh 1997), this study acknowledges the possibility that managerial entrenchment or hubris may influence the selection of targets that are close competitors or

[40] Chen et al. (2021) find a significantly negative association between the interaction term of Q similarity and the number of the target's industry peers and merger likelihood. They interpret the result statistically: a larger pool of potential targets reduces the probability that any specific firm is selected, thereby driving the negative association. I contend that their finding is consistent with the argument and empirical results presented in this study: the substitutability of target resources influences the emergence of positive assortative matching in mergers.
[41] The findings are robust to excluding *TrgQ* from the linear probit model.

geographically proximate, due to bounded rationality (e.g., Jensen 1986; Roll 1986). Conventional wisdom suggests that while operating synergies generate value, mergers driven by entrenchment or hubris often erode shareholder value (e.g., Morck et al. 1990). Therefore, if such managerial motives are present, they would bias the analysis against finding significant positive associations between acquirer shareholder wealth outcomes and either product similarity or geographic proximity.

In arguing the effect of Q similarity on merger outcomes, the theory assumes that these mergers are motivated by value-creating objectives. Under this framework, managerial entrenchment would again bias against detecting significant associations between either Q similarity and either merger likelihood or acquirer shareholder wealth outcomes. However, when acquirer governance is strong (i.e., less entrenched), mergers could also create value by leveraging acquirers' superior, transferable governance resources to manage acquired businesses (Wang and Xie 2009), indicating a negative relationship between Q similarity and merger likelihood (Jovanovic and Rousseau 2002). Among deals involving less entrenched acquirers, two competing forces could drive the relationship between *SimQ* and merger likelihood.

To investigate these, I capture acquirer entrenchment using the E-Index developed by Bebchuk, Cohen, and Ferrell (2009). Following Evgeniou and Vermaelen (2017), E-Index data prior to 2007 are obtained from Professor Lucian A. Bebchuk's website, and post-2007 values are constructed using the ISS ESG Governance database.[42] Requiring non-missing E-Index values reduces the sample of actual mergers to 334 deals. I then construct a binary indicator for high and low levels of acquirer entrenchment, split by the reduced sample median. I replicate the target selection and shareholder wealth effect analyses using the reduced sample and re-conduct the analyses by incorporating the indicator for acquirer entrenchment levels.

Table 15, Panels A and B, reports the results of the target selection analyses. The coefficients on product similarity and geographic proximity remain significantly positive in both the high and low acquirer E-Index subgroups. Geographic proximity is not significantly associated with the likelihood of innovation-driven mergers, regardless of the acquirer's level of

[42] Identifying firm-years requiring supermajority votes for merger approval involves a degree of arbitrariness. The ISS ESG Governance dataset, available from 2007 onward, provides a continuous variable (*SUPERMAJOR_PCT*) but lacks the binary indicator available in the Legacy dataset for earlier years. Following Evgeniou and Vermaelen (2017), I construct a dummy variable equal to one if *SUPERMAJOR_PCT* exceeds 66.7, and zero otherwise.

entrenchment. Thus, the conclusions for ***H1a***, ***H1b***, and ***H2a*** remain robust, whereas the support for ***H2b*** weakens. Specifically, geographic proximity is not significant in the subsample of cost-efficiency-driven mergers in the less entrenched subgroup. Furthermore, the positive effects are more pronounced among acquirers with high managerial entrenchment. This supports the possibility that entrenched acquirers may prefer target firms that share some similarities due to lower information acquisition and processing costs.

Additionally, the positive effect of Q similarity on merger likelihood is significant, primarily driven by the subgroup of highly entrenched acquirers. The patterns align with the competing force speculation in the less entrenched subgroup. Furthermore, the positive effect is significant only in deals aimed at enhancing market position and enriching product portfolios. Hence, the conclusions for ***H3a*** and ***H3b*** remain robust when accounting for acquirer entrenchment.

Table 15, Panels C and D, presents the results of the shareholder wealth effect analyses. The effects of product similarity on acquirer shareholder wealth outcomes remain robust, driven primarily by acquirers with low managerial entrenchment. Product similarity and geographic proximity do not relate to shareholder wealth outcomes in deals led by highly entrenched acquirers. The findings of the effects of *SimQ* on shareholder wealth outcomes indicate that, in deals involving less entrenched acquirers, *SimQ* is positively associated with *AGAIN* and negatively associated with *TCAR* and *TGAIN*. In deals involving highly entrenched acquirers, *SimQ* is positively associated with *CGAIN*. These findings yield two takeaways. First, the results from the low-entrenchment subgroup support the competing force expectation. Second, the positive assortative matching pattern may hold in the high-entrenchment subgroup; however, the expected net gains for acquirer shareholders may not fully materialize if entrenched acquirer management fails to maximize shareholder value in negotiations.

5.6 Robustness Analyses

5.6.1 Assess potential nonlinearity in the relationship between *SimPROD* and merger likelihood

The primary analyses use the product similarity score constructed by Hoberg and Phillip (2010; 2016) to measure product portfolio similarity between firms (*SimPROD*). A conditional logit

model (Model (1)) is estimated to examine the effect of product similarity on merger likelihood. However, residuals from Model (1) remain significantly associated with *SimPROD*, indicating potential model misspecification. To evaluate potential nonlinearity in the relationship between *SimPROD* and merger likelihood, I estimate a linear probit model that adds a quadratic term for *SimPROD* to the specification of Model (1).

Table 16 presents the coefficient estimates. The quadratic term is generally not statistically significant, except in the subsample of innovation-driven mergers. In this subsample, the estimated inflection point lies more than three standard deviations below the subsample mean and below the minimum observed *SimPROD* value (1.53 standard deviations below the mean). These findings indicate that merger likelihood increases monotonically with *SimPROD* across all value-creation subsamples, consistent with the conclusions from the primary analyses.

5.6.2 Alternative measure of product similarity

To further evaluate the robustness of the relationship between product similarity and merger likelihood, I re-estimate Model (1) using an alternative measure of product similarity: *SimNAICS*. *SimNAICS* is a binary indicator equal to one if the (pseudo) merging firms share the same 6-digit NAICS code and zero otherwise.[43] Table 17 reports the coefficient estimates. *SimNAICS* is significantly and positively associated with merger likelihood in the pooled sample of operating synergy-driven mergers, as well as in subsamples focused on improving cost efficiency, enhancing market position, and enriching product portfolios. However, it is statistically insignificant in geographic expansion mergers and innovation-driven mergers, diverging from the results of the primary analyses. Nonetheless, I do not refute the conclusions on H1b but call for caution in interpretation for the following considerations.

This weaker robustness observed in the two subsamples aligns with the notion that geographic market characteristics and technological proximity are the primary drivers of target selection in mergers aimed at geographic market expansion and innovation, respectively. But an indicator variable based on a more granular industry classification (i.e., 6-digit NAICS codes)

[43] NAICS codes are obtained from the Compustat data item *NAICSH*, which defaults to six digits. However, some firm-year observations contain codes of only two to five digits. This study assumes that a firm with a 3-digit NAICS code differs in product portfolio from a firm with a 6-digit code, given the default 6-digit structure. Accordingly, I use the unadjusted *NAICSH* data from Compustat to define the indicator variable *SimNAICS*, which equals one if both firms in a pair share the same NAICSH code, regardless of the code's length, and zero otherwise.

eliminates much of the variation in product similarity captured by *SimPROD*. As a result, replacing the continuous variable with a binary indicator likely reduces the statistical power to detect significant effects of product similarity.

5.6.3 Alternative measure of geographic proximity

I re-estimate Model (2) using an alternative measure of geographic proximity: *SimMSA*, a binary indicator equal to one if firms are headquartered within the same MSA (e.g., Almazan et al. 2010; Bick et al. 2017). Table 18 presents the coefficient estimates. *SimMSA* is significantly positive across all value-creation contexts, except for innovation-driven mergers. These findings are consistent with those from the primary analyses.

5.6.4 Alternative model specification of Model (3)

Concerns arise about the statistical soundness of including *TrgQ* as a control variable while examining the effect of *SimQ*, as the two are mechanically correlated. The evaluation criteria of a possible false positive (Kalnins 2018) are met in the pooled sample of operating synergy-driven mergers and subsamples categorized by enhancing market position and acquiring innovation resources. Therefore, I re-examine the relationship between resource quality similarity and merger likelihood using an alternative specification of Model (3) that excludes *TrgQ*.

Table 19 reports coefficient estimates for this alternative specification. *SimQ* is significantly positive only in the pooled sample of operating synergy-driven mergers and in the subsample of mergers aimed at enriching product portfolios. These results differ from those in the primary analyses and contrast with Chen et al. (2021), who find their results remain robust without controlling for Tobin's Q. Nevertheless, this inconsistency echoes the findings from Section 5.5.6 that the substitutability of target resources moderates the relationship between *SimQ* and merger likelihood, particularly considering that Tobin's Q may incorporate resource scarcity (Rhodes-Kropf and Robinson 2008).

5.6.5 Alternative measure of resource quality similarity

Rhodes-Kropf and Robinson (2008, 1201) note a limitation of their study: "[Q is] an interesting but difficult place to look to understand why mergers are occurring or the value they are creating". This raises concerns about whether the observed "like-buys-like" pattern persists when resource quality is measured independently of market expectations regarding unrealized firm prospects and

merger gains. To address this, I adopt profitability as an alternative proxy for resource quality, following Ahern (2012), to provide additional insights into assortative matching in mergers.

Ahern (2012) argues that a firm's ability to charge a price premium over operating costs reflects its resource quality relative to that of peer firms with similar resources. Accordingly, I use Ahern's profitability measure (*PROF*), defined as net sales minus the cost of goods sold and SG&A expenses, scaled by net sales. SG&A expenses are adjusted following Peters and Taylor (2017).[44] Profitability similarity (*SimPROF*) is measured as the negative absolute difference in *PROF*. A conditional logit model is estimated to examine the effect of *SimPROF* on merger likelihood.

Table 20, Panel A, presents the coefficient estimates. *SimPROF* is positive and significant ($\gamma = 4.06$, $t = 3.89$) only in the subsample of mergers driven by enhancing market position. This finding suggests that, in mergers involving overlapping product or geographic markets, acquirers tend to select target firms with similar profitability levels. Panel B shows that the coefficient for *SimPROF* in this subsample significantly differs from those in other subsamples.

Panel C repeats the analysis of whether the substitutability of target resources affects the relationship between profitability similarity and merger likelihood. *SimPROF* is significantly positive when industry-level profit margin is high, industry-level profit margin heterogeneity is low or moderate, and industry concentration is very low.

The findings related to industry-level profit margin are consistent with the results based on *SimQ*. However, the findings related to industry-level profit margin heterogeneity and industry concentration level diverge from those based on *SimQ*. Importantly, profitability does not incorporate the market expectations of firm prospects. Therefore, in industries with higher heterogeneity or concentration, firms' profitability levels vary more widely, reducing the likelihood of horizontal mergers between similarly profitable firms. The difference in profitability between merging firms in vertical integration is *ex-ante* ambiguous.

Panel D presents coefficient estimates analyzing the impact of *SimPROF* on shareholder wealth outcomes. *SimPROF* is significantly and negatively correlated with *CGAIN*, *AGAIN*, *TCAR*, and *TGAIN*, suggesting that mergers between firms with similar profitability are negatively

[44] SG&A is adjusted following Peters and Taylor (2017), excluding R&D expenses and in-process R&D (XSGA – XRD – RDIP). Two exceptions apply: if R&D exceeds SG&A but remains below the cost of goods sold, SG&A is left unadjusted; and missing values of SG&A, R&D, and in-process R&D are replaced with zeros.

perceived by both acquirer and target shareholders. Panel E shows that *SimPROF* is also negatively related to long-run post-merger performance.

Given prior evidence that financially distressed firms often initiate mergers (Masulis and Simsir 2018), it is plausible that highly profitable firms are less likely to become acquisition targets. If mergers between similarly profitable firms predominantly involve low-profitability acquirers, concerns may arise regarding their ability to manage a larger and more complex organization post-merger. This supports the view that poorly performing firms may pursue acquisitions to obscure underperformance (e.g., Morck et al. 1990).

5.6.6 Exclusion of vertical integrations

Mergers between firms in vertically related industries (hereafter, vertical integrations) likely differ from same-industry horizontal mergers in terms of both interfirm similarity measures and underlying motives. Although this study's theoretical arguments regarding the relationships between interfirm similarity and merger likelihood are not contingent upon distinguishing vertical from horizontal mergers, it may still be warranted to separate them to provide more insights. Additionally, prior studies often operationalize related mergers as same-industry mergers or distinguish vertical from horizontal mergers when examining merger performance. Conducting robustness checks that exclude vertical integrations enhances interpretability and provides methodological consistency with prior studies for some findings in this study.

I re-run the primary analyses after excluding vertical integrations. As shown in Table 21, the main findings remain robust, indicating that vertical integrations do not drive the observed relationships.

5.6.7 Exclusion of deals with extreme price premiums

Mergers characterized by extreme price premiums are unlikely to be motivated by operating synergies or interfirm similarities. In bargain purchases, where the consideration paid is below the target firm's market capitalization, target firms typically lack the bargaining power to negotiate a higher price. In deals involving exceptionally high price premiums, target firms likely possess unique, hard-to-replicate assets, diminishing the relevance of interfirm similarity in target selection.

Price premium (*PREM*) is calculated as the deal value divided by the target's market capitalization 43 trading days prior to the announcement, minus one. To reduce noise from mergers

with extreme price premiums, this subsection re-runs the analyses after excluding such deals. Following Officer (2003) and Cai and Sevilir (2012), I define extreme price premiums as those less than zero or higher than two. The filtered sample comprises 407 actual mergers. As shown in Table 22, the main findings remain robust to this exclusion.

CHAPTER 6 CONCLUSION

6.1 Conclusion

This study yields three principal takeaways. First, pairwise product similarity significantly increases the likelihood of operating synergy-driven mergers. This effect is consistent across different value-creation mechanisms of operating synergies. Product similarity is positively associated with the net present value of the acquirer's expected economic gains from the merger and their relative bargaining power. The relationships are primarily driven by deals where acquirer shareholder rights are strong, suggesting managerial entrenchment reduces negotiation leverage.

Second, geographic proximity increases the likelihood of operating synergy-driven mergers across value-creation sources related to product and geographic markets, but not for mergers targeting innovation resources. The effect is strongest in mergers aimed at geographic expansion. However, geographic proximity is not associated with shareholder wealth outcomes, indicating that capital markets do not consider geographic proximity as a key driver of merger gains or losses or that such information is not new to investors at the time of merger announcements. An exception arises when deals involve both entrenched acquirer management and geographically proximate targets, where the market reacts negatively to merger announcements.

Third, Q similarity is positively associated with the likelihood of operating synergy-driven mergers, particularly those focused on enriching product portfolios. Additional analyses show that this relationship is more pronounced when target resource substitutability is low. Corroborating the argument that Q similarity results from acquirers' tradeoff between synergy generation and distribution to maximize acquirers' expected gains, Q similarity is positively associated with expected synergy and NPV. Notably, when acquirers are less entrenched, Q similarity is not associated with merger likelihood but positively correlates with NPV. In contrast, Q similarity increases merger likelihood in mergers involving entrenched acquirers but is not associated with any shareholder wealth outcomes.

These findings contribute to the M&A literature on resource similarity and resource quality similarity. Collectively, the findings suggest that clarifying the value-creation goals and necessary resources to fulfill the goals is critical to selecting appropriate targets, the starting point of a good

merger. The findings also indicate that requiring disclosure of primary reasons for mergers upon announcements may enhance acquirers' decision-making in operating synergy-driven mergers.

Additionally, this study provides the first direct evidence that public information quality and quantity do not affect the likelihood of related mergers seeking operating synergies, whereas private information channels do. Moreover, this study finds substitution relationships among some private information channels in influencing merger decisions.

6.2 Future Research Opportunities

This study presents several avenues for future research. First, while this study provides insights into the role of product similarity and geographic proximity in influencing acquirers' strategic choices of target firms when pursuing various value-creation sources of operating synergies, it does not investigate factors motivating firms to pursue specific value-creation strategies. A preliminary analysis (Table S2) suggests that the degree of product-market threats may have driven firms to seek specific value-creation opportunities through mergers, warranting further research.

Second, the effect of geographic proximity on merger likelihood depends on the pre-merger geographic distribution of potential merger participants. When suitable targets are geographically distant, acquirers may proactively resort to alternative information channels to identify and evaluate potential targets. Unlike Uysal et al. (2008), who emphasize the role of proximity in synergy identification, this study provides strong evidence that geographic proximity does not influence shareholder wealth outcomes or long-term financial performance. Future work could offer insights into the conditions under which geographic proximity affects merger value.

Third, as Rhodes-Kropf and Robinson (2008) state, the understanding of factors driving Q similarity between merging firms remains limited. This study examines profitability, a concrete dimension of resource quality. Unlike Q similarity, profitability similarity is positively associated with merger likelihood only in mergers aimed at improving market position. It is negatively associated with expected synergy, acquirers' expected net gains, and long-term merger performance, contrasting with the effects of Q similarity. These divergent patterns suggest a need for further exploration of how specific resource quality dimensions drive assortative matching. A direction is asset intangibility. Prior research shows that Tobin's Q can diverge from profitability when asset intangibility is high (Orhangazi 2019; Kilic, Yang, and Zhang 2022).

Additionally, prior studies have linked governance quality to negative assortative matching (Wang and Xie 2009), where firms with dissimilar Qs are more likely to merge (Jovanovic and Rousseau 2002). This study finds that, when acquirers' shareholder rights are strong, both positive and negative assortative matching likely play a role in this merger context, contributing to an insignificant effect on merger likelihood but a positive effect on acquirers' expected net gains. When acquirers' shareholder rights are weak, Q similarity is positively associated with merger likelihood and expected synergy, but it is not associated with either merging party's shareholder wealth outcomes. A closer examination of managerial capability, governance monitoring strength, profitability, and growth opportunities, as well as their interrelationships, may enhance the understanding of how different aspects of resource quality influence matching in M&As.

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Appendix A: Definition of Variables

Variable	Definition	Data Source
Dependent variable of target selection analyses		
DEAL	Dummy variable equal to one if the two firms complete a merger.	SDC
Dependent variables of shareholder wealth effect analyses		
ACAR (TCAR)	ACAR (TCAR) denotes the cumulative abnormal return of the acquirer (target firm) over a three-trading-day window ([-1, +1]) centered on the merger announcement. The event day ([0]) is the merger announcement date if it is a trading day; otherwise, it is the nearest subsequent trading day. Daily abnormal returns are estimated using the market model over a 200-trading-day window ending 43 trading days before the event day. At least 50 trading days within this period must have non-missing, non-zero returns with absolute values no greater than 0.5. Days with missing returns or returns exceeding an absolute value of 0.5 are excluded from the estimation.	SDC; CRSP
CGAIN	CGAIN measures the combined dollar gains to the acquirer and target shareholders around the merger announcement. It is defined as CGAIN = $AME_{-2} \times ACAR + TME_{-2} \times TCAR$, where AME_{-2} is the acquirer's market value of equity two trading days before the announcement, and TME_{-2} is the target's market equity value on the same date, net of the value of any acquirer-held target shares. If AME_{-2} (TME_{-2}) is missing on that date, the value is backward-filled for up to five days; otherwise, AME_{-2} (TME_{-2}) is recorded as missing. ACAR (TCAR) represents the cumulative abnormal returns of the acquirer (target) over the three-trading-day event window centered on the announcement date.	SDC; CRSP
AGAIN	AGAIN represents the acquirer shareholders' expected net present value of merger gains, calculated as AGAIN = $AME_{-2} \times ACAR$. AME_{-2} is the acquirer's market value of equity two trading days before the merger announcement, and ACAR is the acquirer's cumulative abnormal return over the three-trading-day event window.	SDC; CRSP
TGAIN	TGAIN measures the target firm's cumulative abnormal dollar return over a three-trading-day window surrounding the merger announcement. It is calculated as TGAIN = $TME_{-2} \times TCAR$, where TME_{-2} is the target's market value of equity two trading days prior to the merger announcement, and TCAR is the target's cumulative abnormal return over the same event window.	SDC; CRSP
RELTGAIN	RELTGAIN captures the relative bargaining power of the target firm in the distribution of merger synergy value (Ahern 2012). It is calculated as RELTGAIN = (TGAIN – AGAIN) / (AME_{-43} + TME_{-43}), where TGAIN and AGAIN are the cumulative abnormal dollar returns of the target and acquirer, respectively, over a three-trading-day window around the merger announcement. AME_{-43} and TME_{-43} denote the market equity values of the acquirer and target, respectively, as of 43 trading days before the merger announcement. If AME_{-43} (TME_{-43}) is missing on that date, the value is backward-filled for up to five days; otherwise, AME_{-43} (TME_{-43}) is recorded as missing.	SDC; CRSP

Dependent variables of long-term merger performance		
$\Delta ROA[-1,+1]$	The difference between the merged firm's ROA in the first fiscal year following completion and the weighted average ROA of the two merging firms in the fiscal year preceding the merger announcement. Weights are based on each firm's book value of total assets at the fiscal year-end before the announcement.	SDC; Compustat
$\Delta ROA[-1,+2]$	The difference between the merged firm's average ROA over the two post-merger fiscal years and the weighted average ROA of the merging firms in the fiscal year preceding the merger announcement. Weights are assigned based on the firms' book value of total assets at the fiscal year-end before the announcement.	SDC; Compustat
$\Delta ROA[-2,+2]$	The difference between the merged firm's average ROA over the two post-merger fiscal years and the average weighted ROA of the two merging firms over the two fiscal years prior to the announcement. Weights are based on each firm's book value of total assets at the corresponding fiscal year-end.	SDC; Compustat
Firm characteristics		
SIZE	Natural logarithm of the book value of total assets (AT).	Compustat
BHAR	Annual buy-and-hold abnormal returns over the fiscal year before the merger announcement.	CRSP; Compustat
BTM	Book-to-market ratio of equity (BE / ME, where BE = SEQ – PSTK and ME = PRCC_C × CSHO).	Compustat
LEV	The ratio of the sum of short- and long-term debt to the book value of total assets, calculated as (DLTT + DLC) / AT.	Compustat
ROA	Return on assets (OIBDP / AT).	Compustat
Q	The book value of total assets minus the book value of equity plus the market value of equity scaled by the book value of total assets, calculated as (AT – BE + ME) / AT.	Compustat
RETURN	Buy-and-hold abnormal return over the 12 months ending two months prior to the merger announcement month, benchmarked against the value-weighted CSRP index.	CRSP
INSTOWN	Percentage of common shares held by institutional investors in the most recent quarter prior to the merger announcement month, within a 180-day window. Missing values are replaced with zeros.	FactSet Ownership (v5)
FAGE	Natural logarithm of the number of years since the firm's first recorded return in the CRSP monthly data.	CRSP
DACC	Absolute value of performance-matched abnormal discretionary accruals (DACC), as in Karpoff et al. (2013).	Compustat
NonSynchronicity	Stock return non-synchronicity over the calendar year ending June 30 prior to the merger announcement, as in Martin and Shalev (2017).	CRSP

ME	Market value of equity, measured at 43 trading days prior to the merger announcement. For shareholder wealth effect analyses, the SDC DATEANN is adjusted to the announcement date of entering into a definitive merger agreement.	CRSP, SDC, hand-collection
Eindex_HIGH	The Entrenchment Index (E-Index), as defined by Bebchuk et al. (2009), is constructed based on six governance provisions: staggered boards, limits to shareholder bylaw amendments, poison pills, golden parachutes, and supermajority requirements for mergers and charter amendments. • Eindex_HIGH is a dummy variable equal to one if the acquirer's E-Index is above the sample median; zero otherwise.	ISS ESG Governance; Professor Bebchuk's personal website
Pairwise characteristics between firms		
SimPROD	Product similarity score developed by Hoberg and Phillips (2010; 2016), calculated as the cosine similarity of two firms' word choices in business descriptions in 10-K Item 1.	Hoberg–Phillips Data Library
SimNAICS	Indicator variable equal to one if both firms share the same 6-digit NAICS code; zero otherwise.	Compustat
GeoProx	Natural logarithm of one plus the geographic distance between the firms' headquarters. The headquarters are identified based on Compustat zip codes, and the distance is calculated using the Python library *pgeocode*.	Compustat
SimMSA	Indicator variable equal to one if the firms are headquartered in the same metropolitan statistical area (MSA); zero otherwise.	Compustat. The file matching the zip codes to the MSAs is shared by Dr. Tu Nguyen.
SimQ	Primary proxy for resource quality similarity, defined as the negative absolute difference in the natural logarithm of Tobin's Q (Chen et al. 2021).	Compustat
SimPROF	Alternative proxy for resource quality similarity, calculated as the negative absolute difference in (SALE – COGS – SGA_{adj}) / SALE, where SGA_{adj} is the adjusted SG&A expense. The adjustment to Compustat item XSGA follows Peters and Taylor (2017).	Compustat
RelSize	Ratio of the target firm's market value of equity to the acquirer's market value of equity, measured at the end of the fiscal year preceding the merger announcement.	CRSP
D1stConn	Indicator variable equal to one if a director from each firm's board shares a prior professional or educational connection established before the start of the fiscal year preceding the merger announcement. A professional connection exists if both directors have served as executives or board members at the same firm for more than 365 days. An educational connection exists if both directors received the same degree (bachelor's or above) from the same institution within 365 days.	BoardEx

CAudit	Dummy variable equal to one if both firms share the same auditor; zero otherwise.	AuditAnalytics, Compustat, supplemented by hand-collected data from EDGAR
Variables of merger characteristics		
Cash	Dummy variable equal to one if the merger consideration is fully paid in cash; zero otherwise.	SDC
Stock	Dummy variable equal to one if the merger consideration is fully paid in equity; zero otherwise.	SDC
Compete	Dummy variable equal to one if the SDC reports the presence of competing bids for the target firm; zero otherwise.	SDC
Tender	Dummy variable equal to one if the merger is executed through a tender offer; zero otherwise.	SDC
Toehold	Dummy variable equal to one if the acquirer holds some common shares of the target firm preceding the merger announcement; zero otherwise.	SDC
RelDealSize	Ratio of the deal value to the acquirer's market value of equity, measured 43 trading days prior to the merger announcement.	SDC; CRSP
MotiveG	Categorical variable indicating the primary value-creation motive for each merger: 1 = improving cost efficiency (baseline subgroup); 2 = enhancing market position; 3 = enriching product portfolios; 4 = expanding into new geographic markets; 5 = acquiring innovation resources.	Hand-collection
PREM	The price premium variable (PREM) is assigned the first non-missing value among the following three measures, provided the value lies between 0 and 2, inclusive: (1) PREM1: The ratio of the total consideration paid (DEAL_VALUE) to the target firm's market value of equity as of 43 trading days before the merger announcement, minus one. (2) PREM2: The ratio of the initial offer price per share ((PM4WK / 100 + 1) × C4WK) to the target firm's price per share as of 43 trading days before the merger announcement, minus one. (3) PREM3: The ratio of the final offer price per share (PR) to the target firm's price per share as of 43 trading days before the merger announcement, minus one.	SDC; CRSP
Variables indicating industry-level resource substitutability		
ioindPM	Industry-level profitability proxy, calculated as value-added divided by total industry output, based on the BEA USE table	BEA
ioindPMSD	Industry-level profitability heterogeneity, measured as the standard deviation of firm-level profit margins within the IO industry. Profit margin is defined as gross profit divided by net sales.	BEA; Compustat
ioindHHI	Industry concentration ratio, measured by the Herfindahl–Hirschman Index of net sales among all U.S. public firms in each IO industry, based on Compustat sales data.	BEA; Compustat

Appendix B: Matching Procedures

I illustrate several critical considerations and decisions in implementing nearest-neighbor propensity score matching (PSM) below.

a. Propensity score estimation model

I use a logit model to estimate the likelihood that a firm becomes a target in the next fiscal year (the propensity score): $Target = Size + BTM + BHAR + IndFE + YearFE$. The estimation sample includes actual target firm-years and a pool of potential control target firm-years, with each firm-year appearing only once. The predicted propensity scores are saved for the subsequent matching procedure.

b. Caliper distance restriction

The accounting literature lacks a standard guideline for selecting caliper distance. Shipman, Swanquist, and Whited (2016) note that studies using PSM disclose a range of caliper distances, between 0 and 0.23. The choice of caliper distance affects the resulting number of treated observations with at least one matched control. In this study, retaining up to five control target firms, a change in caliper distance from 0.01 to 0.02 does not alter the number of actual target firms with at least one matched control. Since smaller caliper distances generally yield better matches, I adopt a caliper of 0.01. Control target firms must have propensity scores within a caliper of 0.01 of their matched actual target firms' propensity scores.

c. Market capitalization restriction

Matched control firms are required to have market capitalizations within 30% to 300% of their corresponding actual target firms' market capitalizations (Imperatore, Pundrich, Verdi, and Yost 2024).

d. Matching without replacement

Matching is conducted without replacement. Each control firm-year is matched to only one actual target firm-year.

e. Number of control firms

To mitigate confounding from observable covariates, treatment-effect studies often employ one-to-one matching. However, DeFond, Erkens, and Zhang (2016) highlight that using only one control increases sampling variance due to the reduced sample size. This concern is particularly relevant in studies of merger partner selection, where there is limited consensus on the determinants of merger probability, and sample composition can influence conclusions. Accordingly, prior M&A studies rarely match a single control firm to each actual target or acquirer. Following Bena and Li (2014), I match each actual target firm with up to five control firms. Increasing the number of control firms to 10 results in statistically significant differences in *Size* between actual and control target firms, which undermines covariate balance.

f. Assessment of covariate balance

To evaluate matching performance, I present descriptive statistics assessing covariate balance in Table A1. The differences in the three covariates between actual target firms and their matched control counterparts are statistically insignificant.

Table A1: Assessment of matching performance regarding covariate balance between subgroups

	Actual Targets				Control Targets				T-test	Rank-sum test
	N	Mean	SD	Median	N	Mean	SD	Median	(*p*-value)	(*p*-value)
Size	573	7.03	1.76	7.00	2,709	6.95	1.74	6.92	0.310	0.272
BTM	573	0.56	1.16	0.53	2,709	0.57	1.15	0.56	0.789	0.555
BHAR	573	0.00	0.51	-0.07	2,709	0.00	0.44	-0.05	0.787	0.386

Note: *Size* is the natural logarithm of the book value of total assets. *BTM* denotes the book-to-market ratio of equity, where the market value of equity is measured as of the December end of the focal fiscal year. *BHAR* represents the 12-month buy-and-hold abnormal return for the focal fiscal year, requiring at least six months of non-missing return data.

Appendix C: Data Collection and Classification of Merger Motives

C.1 Typology of merger motives

Rabier (2017, 2666) defines "operating synergies [as] gains achieved through the combination of the acquirer's and target's resources. … financial synergies [as] gains achieved through the combination of the acquirer's and target's financial structure." Rabier (2017, Appendix A) categorizes operating synergies into five value-creation motives: "(1) cost reductions through economies of scale or scope, (2) revenue growth through access to the target's product offerings, (3) revenue growth through access to the target's geographic footprint, (4) revenue growth through innovation and the creation of new products, (5) increased market capitalization to reduce competition," and identifies three categories of financial synergies: "(6) financing alternatives, (7) diversification of revenue streams, and (8) market liquidity."

Building on Rabier's (2017) merger motive typology, I classify five value-creation motives of operating synergies: (1) achieving cost efficiency, (2) enhancing market position, (3) enriching product portfolios, (4) expanding into new geographic areas, and (5) acquiring innovations and R&D strengths. During data collection, I identified and excluded mergers motivated by financial synergies. I focus solely on the granular classifications of mergers driven by operating synergies.

C.2 Data collection and cleaning

Data were collected in three rounds, corresponding with the development of the thesis topic and changes in sample selection criteria: (1) April to August 2022, (2) October to November 2022, and (3) December 2024.

(1) First round of data collection

The initial round of data collection, conducted from April to August 2022, involved a sample of 553 mergers. To familiarize myself with relevant data sources, I followed the methodology outlined by Rabier (2017). I randomly selected 100 mergers and examined information about merger background using S-4 filings, press releases, conference call transcripts (or presentation slides), and media coverage to identify merger motives. I also reviewed post-merger 10-K, 10-Q, 10KSB, and 10QSB filings. Because not all mergers involve an S-4 filing, I prioritized press releases, which provide semi-structured and consistently disclosed information. These are typically joint releases containing company overviews, transaction highlights, and the acquirer and

target firms' executive commentary. I treat all commentary except that from target firm executives as reflecting the acquirer's perspective.

Collecting texts relevant to merger motives. I extracted acquirer perspectives on merger goals from three primary sources. First, if available, I used joint press releases announcing definitive agreements. To locate these, I searched for Exhibit 99 attachments in 8-K filings made within three days of the merger announcement date listed in the SDC database via the SEC Analytics Suite. I then manually retrieved the joint press releases. When press releases did not clearly articulate the acquirer's strategic objectives, I examined associated conference call transcripts or PowerPoint presentations. If these were unavailable in EDGAR, I conducted Google searches for alternative sources, prioritizing the acquirer's official media room and then reputable third-party outlets such as Reuters.

I carefully read each text to assess the clarity and content of stated merger motives. For each deal, I extracted relevant text representing the acquirer's objectives. Simultaneously, I conducted a preliminary classification of both pre-merger and post-merger disclosures. The categories included the five operating synergy motives, financial synergies, and a "to be determined (TBD)" category. From the 553 mergers based on pre-merger disclosures, I excluded six driven by financial synergies, one involving a parent-subsidiary combination, and one with indiscernible motives. This left 545 deals for classification. Of the 553 mergers with post-merger disclosures, 426 included relevant motive descriptions, with 197 assigned to the TBD category. Given considerations of data quality, completeness, and representativeness of merger intent (rather than post-hoc justification), I based final classifications on pre-merger disclosures. I compiled an Excel file containing three columns: merger identification number, extracted text, and assigned merger motive classification.

Codifying merger motive classifications. I conducted a second round of merger motive classifications for the 545 mergers using only the extracted texts from pre-merger disclosures. Some texts conveyed multiple value-creation sources. In such cases, I identified the primary motive by evaluating the alignment between the merger's strategic objectives and the value-creation rationale. Upon completing this classification round, I drafted a detailed task instruction document for classifying merger motives (see Appendix C.4).

Next, I hired three undergraduate research assistants (RAs) from a Financial and Management Fellowship program at a Canadian research university. Each RA was trained using the task instruction and completed a pilot task involving 10 sample rows.[45] We discussed and reached a consensus on the classifications for these training cases. Two RAs proceeded to classify the 545 mergers independently as second coders, while I independently classified the same set as another coder. In 256 out of 545 cases, our classifications of the primary motive differed.

To reconcile discrepancies, I enlisted two PhD students in accounting (each assigned 40 rows) and a friend with a bachelor's degree in English and a master's degree in Marketing (assigned 256 rows). They followed the same training protocol. However, one PhD student and the friend misunderstood the task and served effectively as third coders, offering classifications that sometimes differed from both first and second coders. As a result, I treated the 256 rows as having three independent coders. In 67 of these rows, all three coders assigned different primary motives. I resolved these differences based on their classification rationales and made the final classification for each merger. None of the coders were aware of the study's outcomes during the classification process.

(2) Second round of data collection

The second round of data collection was conducted to incorporate 30 newly identified mergers between October and November 2022.

I extracted pre-merger texts reflecting the acquirers' strategic perspectives using the same procedures as described previously. Two other RAs from the same fellowship program were trained using the standard protocol. I served as the first coder, and one RA served as the second coder. For 15 of the 30 rows, our primary motive classifications differed. The second RA reconciled these differences and determined the final classification.

(3) Third round of data collection

The third round was conducted in December 2024 due to revisions in the sample composition. I referenced data records from the first round and included 29 overlapping cases, in which three coders had previously disagreed on the primary motive classification. In this round, I excluded

[45] The third RA worked on classifying post-merger disclosures. However, I chose to focus exclusively on pre-merger disclosure; thus, the post-merger disclosure dataset is excluded from this study.

mergers involving oil and gas firms, as their stated motives often focused on acreage acquisitions or involved regulated assets. After applying all inclusion criteria and excluding cases with missing disclosures or financial synergy motives, the third round included 250 records (some overlapping with the 1st and 2nd rounds).

I extracted pre-merger texts following the established methodology. I then hired three RAs from a strategic management course at a Canadian research university at the end of the semester. After the same training, two RAs independently coded 109 of the 250 rows, while I and the third RA independently coded the remaining 141 rows. I reconciled 108 rows where classifications differed and finalized the coding of merger motives. The division of tasks was based on RA availability.

(4) Summary of data used in this study's sample

Before final inclusion and classification, the sample consisted of 470 deals. I excluded five mergers due to insufficient information to identify the acquirer's motive, one merger motivated by financial synergies, three mergers involving Permian Basin acreage or refinery assets, one merger with a simultaneous announcement of post-merger spin-offs into three businesses, and one merger resulting in a newly created firm and security. Due to the sequential data collection, the number of coders per case varied. I tabulated the frequency distribution of coders and assessed inter-rater consistency using Cronbach's alpha (Cohen 1960) (see Table A2). Inter-rater reliability was high for cases with two or four coders, but lower for those with three or five coders. Cases with three or five coders underwent two rounds of reconciliation. These reconciliations produced a Cronbach's alpha of 0.9631, indicating a high level of agreement. Rabier (2017) considers a value of 0.61 as substantial agreement and 0.84 as perfect agreement.

Table A2: Inter-rater consistency assessment

N_of_coders	N_of_mergers	Cronbach's alpha
2	323	0.7308
3	103	0.4838
4	10	0.7812
5	23	0.3695
Total	459	

C.3 Example excerpts of value-creation motives

1. Improve cost efficiency

   PepsiCo to Buy Two Largest Bottlers, The Pepsi Bottling Group and PepsiAmericas

   If completed, the acquisitions would create a leaner, more agile business model and provide a stronger foundation for PepsiCo's future growth. Upon acquiring the outstanding shares of the two bottlers, PepsiCo would handle distribution of about 80 percent of its total North American beverage volume, including both its direct-store-delivery and warehouse systems.

   PepsiCo Chairman and Chief Executive Officer Indra Nooyi said: "Our operating environment has evolved dramatically in the last decade. Retailers have continued to consolidate. New competitors have emerged. And non-carbonated drinks, which have different economics and different distribution systems than carbonated soft drinks, have become a much bigger factor in the industry and in our own portfolio. We believe that by reshaping our business model we can significantly improve our competitiveness and our growth prospects.

   The consolidation would create annual pre-tax synergies estimated to be more than $200 million, relating primarily to reducing redundant costs, achieving greater scale efficiencies and realizing new revenue opportunities.

2. Enhance market position

   Albemarle Corp to Acquire Rockwood Holdings Inc

   The combination of these two companies creates a premier specialty chemicals company with a unique world-class team of experts and an enhanced focus on innovating customized, performance-based solutions to meet the ever-increasing demands of our customers. ...

   The resulting company will have broader customer reach, increased diversity across end markets, technologies and geographies and more consistent and predictable earnings growth. All four businesses have high margins, strong competitive positions, and attractive long-term growth. The strong cash flows generated by these businesses will enable us to reduce leverage rapidly, support our ongoing dividend payments, and continue investing in the businesses to fuel growth and deliver increased value to our shareholders. ...

   The transaction brings together two of the world's leading specialty chemicals producers with strong market positions. ... On a combined basis, the company is expected to drive growth through: Continuing to penetrate lithium-based energy storage products, including e-mobility batteries and batteries for the automotive industry; Capitalizing on attractive global trends in refinery catalysts, including the increasing demand for transportation fuels particularly in developing regions, as well as the demand for solutions to convert a range of feedstocks into high-value finished products; Expanding within existing bromine markets driven by the proliferation of digital technology, offshore deep water drilling and mercury control emission reduction, along with growth driven by new bromine applications; Leveraging the company's position as a market-leading provider of surface treatment products and services to meet increasing customer demand for products with rigorous quality and performance standards and specifications.

3. Enrich product portfolios

   Cisco Systems, Inc. to Acquire Scientific-Atlanta, Inc.

   "Video is emerging as the key strategic application in the service provider triple play bundle of consumer entertainment, communication and online services," said John Chambers, president and chief executive officer of Cisco Systems. "The combination of Cisco and Scientific-Atlanta brings unmatched experience

and innovation in delivering large scale video systems and networks, and the addition of Scientific-Atlanta further extends Cisco's commitment to and leadership in the service provider market. Moreover, Cisco's international presence and IP leadership will also create strategic synergies that accelerate the combined growth opportunity." Chambers continued, "As consumers demand more sophisticated information and entertainment services in their home, tightly coupled applications, devices and networks will be essential. The collective strength of Linksys and Scientific-Atlanta will extend Cisco's leadership position across the entire networked digital home."

4. Geographic expansion

   Independent Bank Corp to Acquire Peoples Federal Bancshares Inc

   This acquisition will give Rockland Trust its first bank branches in the City of Boston and greatly complements recent expansion initiatives in and around the Boston market. The combining of our two institutions will help unite our steadily growing Eastern Massachusetts footprint, and further strengthen Rockland Trust's position in the attractive Greater Boston metropolitan area.

5. Acquire innovation resources

   Bristol-Myers Squibb Co to Acquire Medarex Inc

   Medarex's technology platform, people and pipeline provide a strong complement to our company's biologics strategy, specifically in immuno-oncology". "With its productive and proven antibody discovery capabilities, ability to generate interesting therapeutic programs and unique set of pre-clinical and clinical assets in development, Medarex represents what we're looking for in terms of our String of Pearls strategy. This acquisition is another important step in our BioPharma transformation." Bristol-Myers Squibb gains the following as a result of the acquisition: Positions Bristol-Myers Squibb for Long-Term Leadership in Biologics; Acquires Proven Antibody Discovery Technology; Gains Full Rights to Promising Phase III Compound, Ipilimumab; Significantly Expands Oncology and Immunology Pipeline.

C.4 Task Instruction

TASK: Categorize the text into one/two major categories of merger motives

OBJECTIVE
For each row, you are given a piece of text describing the motive, the facts, and/or the expected effects of a merger transaction between two companies, from the perspective of the acquiring firm. The task is to classify each transaction (row) into one or two of the five categories of merger motives, which are illustrated as follows:

- **Achieving cost efficiency:** If the text suggests that a transaction is driven by achieving cost efficiency, please classify the transaction into this category. A transaction might achieve cost savings, synergies, or efficiency via economies of scale and scope, bringing business operations under common control (e.g., pre-merger joint ventures or strategic alliances), eliminating redundancies (e.g., acquisition of a direct competitor or a firm in a similar product domain), etc.

- **Geographic expansion:** If the text suggests that the transaction is driven by the goal of entering new geographic areas or expanding the firm's presence in areas where it previously did not have a presence or had an insignificant presence (market share), please classify the transaction into this category. Typical wording might include: "expand into xxx areas"; "add geographic footprint in xxx"; "establish presence in xxx." *xxx* refers to location names such as Boston.

- **Enhance market position:** If the text suggests that the transaction is driven by enhancing or strengthening market position, in terms of either geographic or product markets, please classify the transaction into this category. Typical wording might include increasing the firm's influence or reputation; increasing the prominence of its products, services, or solutions to customers; creating a leading company in an industry; or resulting in the 2nd, 3rd, 5th, etc., largest company in an industry or geographic area. Transactions driven by within-market growth strategies should also be classified into this category.

- **Enrich product portfolio:** If the text suggests that the transaction is driven by the anticipated contribution of the product portfolio(s) of the target firm, please classify the transaction into this category. Typical wording might include enriching the product portfolio, adding product lines or brands, resulting in integrated solutions, or a broad spectrum of product portfolios. The text might also express an expanding footprint in a specific product market.

- **Obtain innovations and R&D strengths:** If the text explicitly emphasizes that the goal is to acquire in-process development products or technologies, near-to-market products, innovations, or innovative and creative products or culture, please classify the transaction into this category.

INSTRUCTIONS

Step 1. Read through this instruction file.

Step 2. Open the Excel file assigned to you.

Step 3. Read the text under column **'mm_ma_text,'** and

- Exercise your judgment based on the above instructions and determine the single major merger motive. Please report it under column **'motive_major'** by selecting from the drop-down list.
- If your judgment indicates that there is another category of motive that could drive the merger, please report it under column **'motive_secondary'**.

Step 4. Please use one or two sentences (excerpts) to briefly illustrate or support your classification. These sentences may be partial excerpts from the text or your own words.

ADDITIONAL NOTE

In some cells, there are 'HEADER,' 'Highlight(s)', and 'TEXT' subsections. The sentences or words in these three sections are not more prominent than one another. Thus, please do not decide solely based on the sentence following 'HEADER' or 'Highlight(s)'. However, sentences indicating that the transaction is "consistent with strategy" or "stated goal of …" may reflect more prominent information for your judgment.

Appendix D: Supplemental Materials

S1: Operationalization of Related Industries and Industry Mapping

S1.1 Operationalization of related industries

This thesis defines firms in related industries as those operating within the same industry or across two distinct but vertically related industries. I classify two industries as vertically related if one purchases at least 5% of its inputs from, or sells at least 5% of its outputs to, the other, and vice versa (Haunschild 1993; 1994). I measure vertical relatedness using the Input-Output (IO) Accounts Data from the U.S. Bureau of Economic Analysis (BEA), reported annually at the summary level.[46] These summary-level datasets include 66 industry groups, excluding five codes that represent state and government sectors. Its granularity (71 codes) closely matches that of the 2-digit Standard Industrial Classification system (83 codes), which many prior M&A studies use to differentiate between related and unrelated mergers.

To identify related industry pairs for each year from 1997 to 2022, I follow these steps:

Step 1. Construct a 66 × 66 matrix ($Supply_j \times Use_k$) that reports the dollar value of commodities flowing from supply industry *j* (row) to use industry *k* (column):

- I begin by retrieving the BEA SUPPLY table, which lists domestic commodity supply by industry. In this table, the row and column labels follow the same classification scheme. Each cell shows the dollar value of a given commodity (row) produced by a specific industry (column). I replace missing values with zeros and divide each cell by the total product supply at basic prices (column T013), which includes both domestic output and imports. I then retain data on the 66 relevant commodities and industries. After transposing the table, I obtain a 66 × 66 matrix ($Supply_j \times Commodity_i$), where each cell reflects the percentage of a given commodity (column) supplied by domestic firms in each industry (row). I refer to this matrix as ***pct_SUP***.
- Next, I retrieve the BEA USE table, which reports the use of commodities by industry. Again, the row and column labels follow the same classification scheme. Each cell reports

[46] The BEA reference year for monetary values in the SUPPLY and USE tables has been updated. See https://www.bea.gov/node/20871. These changes, however, should have minimal effect on the percentage-based metrics used in this study. I downloaded the summary-level data files covering 1997–2020 on February 8, 2022, and those covering 2017–2022 on September 12, 2023.

the dollar value of a given commodity *i* (row) purchased by industry *k* (column). I replace missing values with zeros and retain data for the 66 relevant commodities and industries. This yields a 66 × 66 matrix ($Commodity_i \times Use_k$), where each cell reports the dollar amount of a given commodity used by industry *k*. I refer to this matrix as ***USE***.

- I multiply ***pct_SUP*** by ***USE*** to produce a 66 × 66 matrix ($Supply_j \times Use_k$), where each cell captures the estimated dollar flow of commodities from industry *j* (row) to industry *k* (column).

Step 2. Define upstream and downstream industries for each focal industry

- I classify industry *j* as an *upstream industry* to focal industry *k* if *k* purchases at least 5% of its total inputs from *j*. I refer to this percentage as ***pct_purchase***.
- I classify industry *j* as a downstream industry to focal industry *k* if *k* sells at least 5% of its total outputs to *j*. I denote this percentage as ***pct_sales***.

Step 3. Given the $Supply_j(66) \times Use_k(66)$ matrix, ***pct_purchase*** and ***pct_sales*** are calculated as follows:

- For ***pct_purchase***, I divide each cell by the total of its column (i.e., the summation across all rows for its column: total inputs of industry *k*). This yields the share of inputs that *k* sources from *j*. I retain only industry pairs where the value is ≥ 0.05 and store them as arrays of focal industry *k* and its upstream industry *j*.
- For ***pct_sales***, I divide each cell by the total of its row (i.e., the summation across columns for its row: total outputs of industry *j*). This gives the share of outputs that *j* sells to *k*. I retain only industry pairs with values ≥ 0.05 and store them as arrays of focal industry *j* and its downstream industry *k*.

Step 4. I append an array of same-industry pairs for each of the 66 IO industries per year and eliminate duplicate rows.

Step 5. I repeat steps 1 through 4 for each year from 1997 to 2022.

Step 6. I exclude any industry pairs for which I cannot map the IO codes to the corresponding Compustat NAICSH codes.

S1.2 Industry mapping

I map NAICSH codes to IO industry codes in the following steps:

- I first construct a correspondence table between IO industry codes and 2-, 3-, or 4-digit 2012 NAICS codes based on the file "*Use_SUT_Framework_2007_2012_DET.*"[47] I consolidate the IO industry codes "HS" and "ORE" into a single category that maps to the 2012 NAICS code "531". I also update the table by adding mappings for "513" → "513" and "514" → "514." Table S1-1 shows the resulting concordance table.
- Second, I track changes in 6-digit NAICS codes across different versions of the NAICS manual, released every five years, based on the NAICS concordance tables provided by the U.S. Census Bureau.[48] Table S1-2 summarizes the changes that result in reclassification at the 3- or 4-digit level, which influences the mapping to IO industry codes. I exclude one mapping line to prevent ambiguity. Without this exclusion, the 2002 NAICS code "339" would map both "333" and "337" in the 2012 NAICS system.
- Third, I convert Compustat NAICSH codes to 2012 NAICS codes across three time periods. For the period through 2006, I use the "From 2012 to 2002" conversion table, assuming Compustat followed the 2002 NAICS manual. For 2007–2011, I apply the "From 2012 to 2007" table, assuming the use of the 2007 NAICS manual. For 2012 onward, I assume that Compustat adopted the 2012 and 2017 NAICS manuals. I exclude any Compustat observations where the NAICSH code does not appear in the NAICS–IO concordance tables.

[47] I downloaded the Excel file used in data construction for this study on September 29, 2021.
[48] See https://www.census.gov/naics/?68967.

Table S1-1: Concordance Table of IO Industry Codes and 2012 NAICS

IO Industry Code Summary Level	2012 NAICS Code	Industry Description
111CA	111, 112	Farms
113FF	113-115	Forestry, fishing, and related activities
211	211	Oil and gas extraction
212	212	Mining, except oil and gas
213	213	Support activities for mining
22	22	Utilities
23	23	Construction
321	321	Wood products
327	327	Nonmetallic mineral products
331	331	Primary metals
332	332	Fabricated metal products
333	333	Machinery
334	334	Computer and electronic products
335	335	Electrical equipment, appliances, and components
3361MV	3361-3363	Motor vehicles, bodies and trailers, and parts
3364OT	3364-3366, 3369	Other transportation equipment
337	337	Furniture and related products
339	339	Miscellaneous manufacturing
311FT	311, 312	Food and beverage and tobacco products
313TT	313, 314	Textile mills and textile product mills
315AL	315, 316	Apparel and leather and allied products
322	322	Paper products
323	323	Printing and related support activities
324	324	Petroleum and coal products
325	325	Chemical products
326	326	Plastics and rubber products
42	42	Wholesale trade
441	441	Motor vehicle and parts dealers
445	445	Food and beverage stores
452	452	General merchandise stores
4A0	442-444, 446-448, 451, 453, 454	Other retail stores
481	481	Air transportation
482	482	Rail transportation
483	483	Water transportation
484	484	Truck transportation
485	485	Transit and ground passenger transportation
486	486	Pipeline transportation
487OS	487, 488, 492	Other transportation and support activities
493	493	Warehousing and storage
511	511	Publishing industries (includes software)
512	512	Motion picture and sound recording industries
513	515, 517, 513	Broadcasting and telecommunications
514	518, 519, 514	Data processing, internet printing, and all other information services
521CI	521, 522	Federal Reserve banks, credit intermediation, and related activities
523	523	Securities, commodity contracts, and investments
524	524	Insurance carriers and related activities
525	525	Funds, trusts, and other financial vehicles
HS, ORE	531	Housing and other real estate

532RL	532, 533	Rental and leasing services and lessors of intangible assets
5411	5411	Legal services
5415	5415	Computer systems design and related services
5412OP	5412-5414, 5416-5419	Miscellaneous professional, scientific, and technical services
55	55	Management of companies and enterprises
561	561	Administrative and support services
562	562	Waste management and remediation services
61	61	Educational services
621	621	Ambulatory healthcare services
622	622	Hospitals
623	623	Nursing and residential care facilities
624	624	Social assistance
711AS	711, 712	Performing arts, spectator sports, museums, and related activities
713	713	Amusements, gambling, and recreation industries
721	721	Accommodation
722	722	Food services and drinking places
81	81	Other services, except government

Table S1-2: Documentation of Cross-Year NAICS Changes

From 2012 to 2017 NAICS

Based on the concordance table "2012_to_2017_NAICS"

There is no change.

From 2012 to 2007 NAICS

Based on the concordance table "2012_to_2007_NAICS"

2012 NAICS	2012 NAICS – My code	2007 NAICS	2007 NAICS – My code
321999	321	337129	337
333316	333	*334119*	334
443142	443	451220	451

From 2012 to 2002 NAICS

Based on the concordance tables "2012_to_2007_NAICS" and "2007_to_2002_NAICS"

2012 NAICS	2012 NAICS – My code	2007 NAICS	2007 NAICS – My code	2002 NAICS	2002 NAICS – My code
112519	112	*112519*	112	*111998*	111
314999	314	*314999*	314	*315211*	315
314999	314	*314999*	314	*315212*	315
333249	333	*333298*	333	*339111*	339
333415	333	*333415*	333	*339111*	339
333994	333	*333994*	333	*339111*	339
333997	333	*333997*	333	*339111*	339
333999	333	*333999*	333	*339111*	339
336612	3366	*336612*	3366	*326199*	326
336612	3366	*336612*	3366	*326299*	326
~~*337127*~~	~~337~~	~~*337127*~~	~~337~~	~~*339111*~~	~~339~~
517110	517	*517110*	517	*518111*	518
517919	517	*517919*	517	*518111*	518
519130	519	*519130*	519	516110	516
519130	519	*519130*	519	518112	518
531110	5311	*531110*	5311	*525930*	525
531120	5311	*531120*	5311	*525930*	525
531130	5311	*531130*	5311	*525930*	525
531190	5311	*531190*	5311	*525930*	525
561312	561	*561312*	561	*541612*	5416

Note: Refer to the U.S. Census Bureau NAICS concordance (see https://www.census.gov/naics/?68967) for the data source.

S2: Table S2: Effect of Product-Market Threat Similarity on Merger Likelihood

Table S2 examines the effect of product-market threat similarity on the likelihood of mergers motivated by distinct value-creation objectives related to operating synergies.

Panel A presents coefficient estimates from the following conditional logit model, which examines the effect of product-market threat similarity on the likelihood of mergers driven by operating synergies.

$$Deal = \gamma_1 SimFLUID + \gamma_2 TrgFLUID + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgQ + \beta_4 TrgRETURN + \beta_5 TrgLEV + \beta_6 TrgINSTOWN + \beta_7 TrgROA + \beta_8 TrgFAGE + GroupFE$$

The dependent variable (***Deal***) equals one if the observation refers to an actual merger and zero otherwise. ***SimFLUID*** is defined as the absolute difference in the product-market threat proxy developed by Hoberg et al. (2014). ***TrgFLUID*** denotes the level of product-market threat faced by the target firm (Hoberg et al. 2014). ***RELSIZE*** is a proxy for the relative size of the target firm to the acquirer, measured as the market capitalization of the (control) target firm relative to that of the acquirer. Several control variables are included to account for target firm characteristics: ***TrgSIZE***, the natural logarithm of the book value of total assets; ***TrgQ***, the market-to-book value of total assets; ***TrgRETURN***, the 12-month buy-and-hold cumulative abnormal return relative to the CRSP market index, measured over 12 months ending at two months prior to the merger announcement; ***TrgLEV***, the financial leverage ratio, calculated as the sum of current and long-term debt scaled by total assets; ***TrgINSTOWN***, the percentage of institutional ownership; ***TrgROA***, return on assets, measured as operating income before depreciation scaled by total assets; and ***TrgFAGE***, firm age, calculated as the natural logarithm of the number of years since the firm's first appearance in the CRSP monthly data.

Column titles indicate different estimation samples: column (1) presents results based on the pooled sample of operating synergy-driven mergers; columns (2) through (6) present results for subsamples categorized by distinct value-creation motives, including (2) improving cost efficiency, (3) enhancing market position, (4) enriching product portfolios, (5) geographic market expansion, and (6) acquiring innovation resources.

Panel B reports *p*-values from Wald tests assessing whether the coefficients on ***SimFLUID*** across subgroup analyses from Panel A, columns (2)–(6), differ significantly from one another (i.e., whether their confidence intervals do not overlap). For instance, the test comparing column (2) versus column (3) yields a *p*-value of 0.255, indicating that the estimated effects of product-market threat similarity on merger likelihood do not differ significantly between mergers motivated by cost efficiency improvements and those seeking market position enhancements.

All continuous variables are winsorized at the 1st and 99th percentiles based on the pooled sample. These variables are then standardized by subtracting the mean and dividing by the standard deviation of the estimation sample in each analysis. Standard errors are clustered at the matched actual-control merger group level, and *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table S2, continued

Panel A: Coefficient estimates for conditional logit models analyzing the effect of product-market threat similarity on merger likelihood

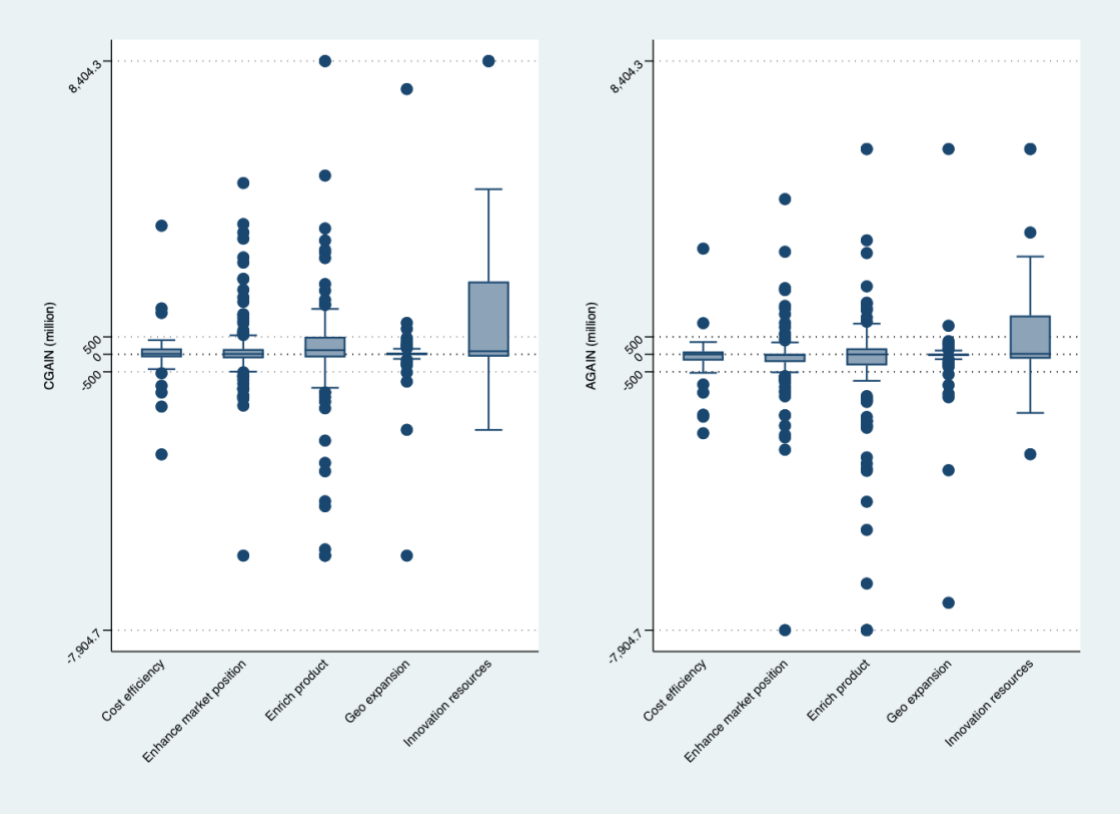
	(Pooled sample)	(Cost efficiency)	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
	(1)	(2)	(3)	(4)	(5)	(6)
SimFLUID	**0.31*****	0.38	0.05	**0.55*****	**0.41****	**0.89*****
	(4.24)	(1.40)	(0.52)	(4.19)	(2.16)	(2.84)
TrgFLUID	0.40***	0.66*	0.15	0.56***	0.29	1.05**
	(4.34)	(1.76)	(1.18)	(3.55)	(1.37)	(2.07)
RelSIZE	-0.56***	-0.99**	-0.61***	-0.32**	-0.57**	-0.59
	(-5.41)	(-2.53)	(-3.53)	(-2.00)	(-2.10)	(-1.18)
TrgSIZE	1.01***	3.39***	1.18***	0.21	0.69	0.85
	(4.34)	(3.11)	(2.86)	(0.54)	(1.50)	(1.27)
TrgQ	0.30***	0.49	0.17	0.19	-0.07	0.45
	(3.53)	(1.37)	(1.46)	(1.21)	(-0.47)	(1.34)
TrgRETURN	0.01	-0.32	-0.15	0.10	0.17	0.02
	(0.20)	(-1.51)	(-1.26)	(0.91)	(1.26)	(0.11)
TrgLEV	-0.09	0.26	-0.13	-0.06	-0.21	-0.38
	(-1.38)	(0.88)	(-1.31)	(-0.44)	(-1.46)	(-1.40)
TrgINSTOWN	0.52***	0.74	0.45***	0.76***	0.16	0.68*
	(6.00)	(1.43)	(3.24)	(5.28)	(0.80)	(1.69)
TrgROA	-0.03	-0.34	0.20*	0.30**	0.18	-0.79**
	(-0.42)	(-1.22)	(1.71)	(2.34)	(0.95)	(-2.49)
TrgFAGE	-0.04	-0.08	-0.08	-0.23**	0.40**	-0.23
	(-0.72)	(-0.37)	(-0.78)	(-2.11)	(2.51)	(-0.91)
N of Obs.	2,619	201	953	807	447	211
N of Groups	459	35	164	142	80	38
Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.07	0.24	0.04	0.13	0.08	0.30
Model test *p*-value	0.00	0.06	0.00	0.00	0.01	0.00
Link Test						
p-value of _hat	0.000	0.000	0.000	0.000	0.000	0.000
p-value of _hatsq	0.493	0.322	0.757	0.750	0.859	0.737

Panel B: Wald tests of pairwise differences in the coefficients on *SimFLUID* across subgroup analyses

Wald test *p*-values are reported.	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
	(3)	(4)	(5)	(6)
(1) Cost efficiency	0.255	0.575	0.946	0.222
(2) Market position		**0.003**	**0.100**	**0.011**
(3) Product portfolio			0.521	0.320
(4) Geo expansion				0.184

Figure 1: Box Plots of CGAIN, AGAIN, and ACAR

Figure 1 presents the box plots of ***CGAIN***, ***AGAIN***, and ***ACAR*** across the five value-creation motives based on 452 operating synergy-driven mergers with available data on shareholder wealth outcome measures. ***CGAIN*** captures the expected merger synergy, ***AGAIN*** measures the net present value of the acquirer's expected gains from the merger, and ***ACAR*** measures the three-trading-day cumulative abnormal percentage returns surrounding the merger announcement. The three variables are winsorized at the 1st and 99th percentiles based on the 452 mergers used in shareholder wealth effect analyses.



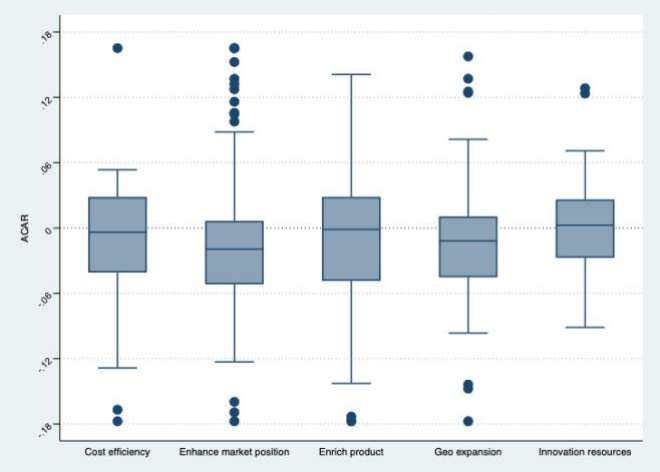


Table 1: Sample Description

Table 1, **Panel A**, outlines the sample selection criteria used to identify actual mergers included in the primary analyses of target selection. **Panels B**, **C**, and **D** present the frequency distribution of these mergers by the BEA Input-Output (IO) sector-level industry classification, merger announcement year, and primary value-creation motive, respectively.

Panel A: Summary of sample selection criteria

Sample selection criteria	**N of mergers**
Initial screen of mergers based on Refinitiv SDC M&A dataset[a]	
• Merger format is "Merger" or "ACQ of Majority Interest".	
• Both the acquirer and the target are U.S. public firms with non-missing CUSIP identifiers.	
• The acquirer holds less than 50% of the target's shares pre-merger and seeks to own 100% post-merger.	
• Deal value (SDC item DEAL_VALUE) is larger than either $10 million or 1% of the acquirer's pre-merger firm value (SDC item AMV). The target share price four weeks prior to the merger announcement is larger than $1.	
• The merger is marked "Completed" with a non-missing effective date.	
• The deal is not classified as a divestiture, repurchase, recapitalization, restructuring, spin-off, or acquisition of a subsidiary.	5,224
• For serial acquisitions, defined by a series of five or more completed mergers announced by the same acquirer within three calendar years, only the first announced merger is retained.	5,013
Further data requirements	
• Both the acquirer and the target have available data for the fiscal year prior to the merger announcement, based on the intersection of Compustat and CRSP. Only firm-years with single-class securities listed on the NYSE, AMEX, or NASDAQ are included.	3,074
• The fiscal year prior to the merger announcement falls between 2003 and 2021 for both acquirer and target firms.	1,247
• Both the acquirer and the target have non-missing NAICSH codes in Compustat that can be mapped to BEA IO industry classification codes.	1,242
• Only related mergers are retained.	1,041
• Both the acquirer and the target have non-missing BoardEx data for the fiscal year before the merger announcement.	790
Preliminary sample of mergers	**790**
Further data requirements	
• Both the acquirer and the target have non-missing values for all control variables measured at the fiscal year-end prior to the merger announcement.	586
• Each observed target firm must have at least one matched control firm.	573
• Firm-pair measures and other control variables must be non-missing	555
Further data requirements	
• Mergers involving acquirers or targets in the oil, gas, and utilities industries, or firms whose core business involves investing (based on a list of SIC codes defined by de Groote et al. 2021), are excluded.	491
• Using hand-collected data for deals announced through December 31, 2021, mergers lacking a clearly identifiable value-creation motive related to operating synergies are excluded.	459
Final sample of actual mergers included in the primary analyses of target selection	**459**

[a] The Refinitiv SDC M&A dataset was downloaded from WRDS on July 15, 2024.

Table 1, continued

Panel B: Frequency distribution of sample mergers by IO industry at the sector level

IO-Sector	Industry Label	By target Industry N of mergers	By target Industry % of sample	By acquirer Industry N of mergers	By acquirer Industry % of sample
11	Agriculture, forestry, fishing, and hunting	1	0.22	1	0.22
23	Construction	2	0.44	2	0.44
31ND	Nondurable goods	69	15.03	71	15.47
33DG	Durable goods	93	20.26	93	20.26
42	Wholesale trade	7	1.53	9	1.96
44RT	Retail trade	12	2.61	13	2.83
48TW	Transportation and warehousing, excluding postal service	3	0.65	3	0.65
51	Information	42	9.15	45	9.8
52	Finance and insurance	191	41.61	186	40.52
53	Real estate and rental and leasing	6	1.31	8	1.74
54	Professional and technical services	12	2.61	6	1.31
56	Administrative and waste services	6	1.31	5	1.09
62	Health care and social assistance	8	1.74	10	2.18
71	Arts, entertainment, and recreation	2	0.44	2	0.44
72	Accommodation and food services	4	0.87	4	0.87
81	Other services, except government	1	0.22	1	0.22
Total		459	100	459	100

Panel C: Frequency distribution of sample mergers by the calendar year of the merger announcement

Year	N of mergers	% of sample	Year	N of mergers	% of sample
2004	10	2.18	2013	31	6.75
2005	14	3.05	2014	27	5.88
2006	30	6.54	2015	36	7.84
2007	43	9.37	2016	29	6.32
2008	29	6.32	2017	27	5.88
2009	17	3.7	2018	24	5.23
2010	33	7.19	2019	25	5.45
2011	17	3.7	2020	10	2.18
2012	32	6.97	2021	25	5.45

Panel D: Frequency distribution of sample mergers by the acquirer's primary value-creation motive

Merger motive	N of mergers	% of sample
Improve cost efficiency	35	7.63
Enhance market position	164	35.73
Enrich product portfolios	142	30.94
Expand into new geographic markets	80	17.43
Acquire innovation resources	38	8.28
Total	459	100

Table 2: Descriptive Statistics of Variables in Primary Analyses Based on the Pooled Sample

Table 2 presents descriptive statistics for variables included in Models (1), (2), and (3), which analyze acquirers' target selection. The estimation sample comprises 459 matched groups of actual-control mergers, forming a pooled dataset of 2,619 firm pairs. For each actual merger, the control group is constructed by pairing the actual acquirer with up to five control target firms.

Panel A presents summary statistics of explanatory variables for the subgroup of actual mergers and the subgroup of control mergers, including the number of observations, mean, standard deviation, and median, as well as univariate analyses testing whether the value distribution of each variable differs significantly between the two subgroups. Student's *t*-tests are used to assess differences in means, while Wilcoxon rank-sum tests evaluate differences in medians. The last two columns report the mean differences and the *p*-values from the median difference tests.

Panel B provides summary statistics for all variables included in Models (1), (2), and (3), including the number of observations, mean, and standard deviation, as well as Pearson and Spearman correlation matrices.

SimPROD is a proxy for product similarity, measured as the cosine similarity of two firms' word usages in business descriptions, developed by Phillips and Hoberg (2010; 2016). ***GeoProx*** is a proxy for geographic proximity, calculated as the negative natural logarithm of one plus the geographic distance between firms' headquarters. ***SimQ*** is a proxy for resource quality similarity, measured as the negative absolute difference in the natural logarithm of Tobin's Q. ***RELSIZE*** is a proxy for the relative size of the target firm to the acquirer, measured as the market capitalization of the (control) target firm relative to that of the acquirer. ***TrgSIZE*** is a proxy for the (control) target firm's asset size, measured as the natural logarithm of the book value of total assets. ***TrgQ*** represents the (control) target firm's Tobin's Q, measured as the market-to-book value of total assets. ***TrgRETURN*** is a proxy for the (control) target firm's stock return performance over the past year, measured as the 12-month buy-and-hold cumulative abnormal return relative to the CRSP market index, as of two months prior to the merger announcement. ***TrgLEV*** denotes the (control) target firm's financial leverage, measured as the sum of current and long-term debt scaled by the book value of total assets. ***TrgINSTOWN*** represents the (control) target firm's institutional ownership. ***TrgROA*** denotes the (control) target firm's return on assets, measured as the operating income before depreciation scaled by the book value of total assets. ***TrgFAGE*** represents the (control) target firm's age, measured as the natural logarithm of the number of years since the firm's first appearance in the CRSP monthly data.

All continuous variables are winsorized at the 1st and 99th percentiles based on the pooled sample. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2, continued

Panel A: Descriptive statistics of explanatory variables by actual and control mergers

	Actual mergers				Control mergers				T-test	Rank-sum test
Variable	N	Mean	SD	Median	N	Mean	SD	Median	dif. in mean	*p*-value
SimPROD	459	0.19	0.08	0.19	2,160	0.13	0.09	0.12	**-0.062*****	**0.000**
GeoProx	459	-5.66	2.15	-6.21	2,160	-6.90	1.27	-7.07	**-1.240*****	**0.000**
SimQ	459	-0.29	0.32	-0.14	2,160	-0.30	0.34	-0.14	-0.012	0.651
RELSIZE	459	0.26	0.29	0.16	2,160	0.28	0.34	0.15	0.016	0.686
TrgSIZE	459	6.87	1.67	6.82	2,160	6.80	1.66	6.78	-0.068	0.399
TrgQ	459	1.80	1.28	1.22	2,160	1.72	1.15	1.20	-0.08	0.516
TrgRETURN	459	0.02	0.43	-0.04	2,160	0.00	0.38	-0.03	-0.017	0.943
TrgLEV	459	0.18	0.20	0.11	2,160	0.17	0.19	0.11	-0.006	0.598
TrgINSTOWN	459	0.64	0.30	0.71	2,160	0.59	0.32	0.61	**-0.057*****	**0.001**
TrgROA	459	0.04	0.15	0.03	2,160	0.04	0.15	0.03	0.007	0.242
TrgFAGE	459	2.36	0.94	2.48	2,160	2.43	0.98	2.64	0.071	**0.060**

Panel B: Summary statistics and Pearson (lower-left) and Spearman (upper-right) correlation coefficients

Variable	N	Mean	SD	(1)	(2)	(3)	(4)	
(1) Deal	2,619	0.18	0.38	1	0.25***	0.23***	0.01	
(2) SimPROD	2,619	0.14	0.09	0.25***	1	0.23***	0.50***	
(3) GeoProx	2,619	6.68	1.54	0.31***	0.20***	1	0.18***	
(4) SimQ	2,619	-0.30	0.34	0.01	0.41***	0.08***	1	
(5) RELSIZE	2,619	0.27	0.33	-0.02	0.09***	0.02	0.08***	
(6) TrgSIZE	2,619	6.81	1.66	0.02	0.31***	0.09***	0.33***	
(7) TrgQ	2,619	1.74	1.18	0.03	-0.28***	-0.02	-0.49***	
(8) TrgRETURN	2,619	0.00	0.39	0.02	-0.01	-0.04*	-0.04*	
(9) TrgLEV	2,619	0.17	0.20	0.01	-0.13***	0.01	-0.05*	
(10) TrgINSTOWN	2,619	0.60	0.32	0.07***	-0.29***	-0.04*	-0.20***	
(11) TrgROA	2,619	0.04	0.15	-0.02	-0.20***	0.02	0.05**	
(12) TrgFAGE	2,619	2.41	0.97	-0.03	-0.13***	0.02	-0.00	
Variables	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Deal	0.01	0.02	0.01	-0.00	0.01	0.06**	-0.02	-0.04
(2) SimPROD	0.17***	0.29***	-0.46***	0.00	-0.05*	-0.29***	-0.40***	-0.14***
(3) GeoProx	0.05*	0.14***	-0.14***	-0.02	0.03	-0.11***	-0.07***	0.03
(4) SimQ	0.17***	0.36***	-0.50***	0.00	0.01	-0.30***	-0.26***	-0.01
(5) RELSIZE	1	0.37***	-0.07***	0.08***	0.13***	0.12***	0.12***	0.07***
(6) TrgSIZE	0.31***	1	-0.31***	0.03	0.37***	0.26***	0.14***	0.21***
(7) TrgQ	-0.02	-0.34***	1	0.06**	-0.03	0.38***	0.33***	0.00
(8) TrgRETURN	0.06**	0.00	0.09***	1	-0.02	0.08***	0.10***	0.07***
(9) TrgLEV	0.10***	0.26***	0.01	-0.04	1	0.17***	0.21***	0.06**
(10) TrgINSTOWN	0.16***	0.30***	0.22***	0.09***	0.20***	1	0.41***	0.15***
(11) TrgROA	0.10***	0.27***	-0.15***	0.08***	0.11***	0.25***	1	0.23***
(12) TrgFAGE	0.06**	0.19***	-0.07***	0.04	0.02	0.15***	0.21***	1

Table 3: Descriptive Statistics of Variables in Primary Analyses Based on Distinct Merger Motive Subsamples

Table 3 presents descriptive statistics for variables included in Models (1), (2), and (3) based on subsamples of the 459 matched actual-control mergers, categorized by five distinct value-creation motives. For each actual merger, the control group is constructed by pairing the actual acquirer with up to five control target firms. The five value-creation motives include: improving cost efficiency, enhancing market position, enriching product portfolios, expanding into new geographic markets, and acquiring innovation resources.

Panel A presents summary statistics of explanatory variables for the subgroup of actual mergers and the subgroup of control mergers, including the number of observations, mean, standard deviation, median, as well as results from univariate tests of whether each variable's value distribution significantly differs between the two subgroups. Student's *t*-tests are used to assess differences in means, while Wilcoxon rank-sum tests evaluate differences in medians. The last two columns report the mean differences and the *p*-values from the median difference tests.

Panel B presents summary statistics for all variables included in Models (1), (2), and (3), including the number of observations, mean, and standard deviation, as well as Pearson correlation matrices.

SimPROD is a proxy for product similarity, measured as the cosine similarity of two firms' word usages in business descriptions, developed by Phillips and Hoberg (2010; 2016). ***GeoProx*** is a proxy for geographic proximity, calculated as the negative natural logarithm of one plus the geographic distance between firms. ***SimQ*** is a proxy for resource quality similarity, measured as the negative absolute difference in the natural logarithm of Tobin's Q. ***RELSIZE*** is a proxy for the relative size of the target firm to the acquirer, measured as the market capitalization of the (control) target firm relative to that of the acquirer. ***TrgSIZE*** is a proxy for the (control) target firm's asset size, measured as the natural logarithm of the book value of total assets. ***TrgQ*** represents the (control) target firm's Tobin's Q, measured as the market-to-book value of total assets. ***TrgRETURN*** is a proxy for the (control) target firm's stock return performance over the past year, measured as the 12-month buy-and-hold cumulative abnormal return relative to the CRSP market index, as of two months prior to the merger announcement. ***TrgLEV*** denotes the (control) target firm's financial leverage, measured as the sum of current and long-term debt scaled by the book value of total assets. ***TrgINSTOWN*** represents the (control) target firm's institutional ownership. ***TrgROA*** denotes the (control) target firm's return on assets, measured as the operating income before depreciation scaled by the book value of total assets. ***TrgFAGE*** represents the (control) target firm's age, measured as the natural logarithm of the number of years since the firm's first appearance in the CRSP monthly data.

All continuous variables are winsorized at the 1st and 99th percentiles based on the pooled sample. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Descriptive statistics of explanatory variables based on subsamples driven by distinct value-creation motives

	Actual mergers				Control mergers				T-test	Rank-sum test
Variable	N	Mean	SD	Median	N	Mean	SD	Median	dif. in mean	*p*-value
Motive = Improve cost efficiency										
SimPROD	35	0.17	0.08	0.13	166	0.11	0.09	0.08	**-0.067*** **	**0.000**
GeoProx	35	-5.40	2.88	-6.90	166	-7.11	1.22	-7.35	**-1.709*** **	**0.001**
SimQ	35	-0.38	0.34	-0.20	166	-0.36	0.38	-0.19	0.013	0.598
RELSIZE	35	0.26	0.25	0.21	166	0.29	0.33	0.17	0.03	0.913
TrgSIZE	35	6.70	1.64	6.67	166	6.42	1.50	6.44	-0.276	0.325
TrgQ	35	1.78	1.17	1.40	166	1.75	1.08	1.39	-0.03	0.758
TrgRETURN	35	-0.06	0.30	-0.10	166	0.00	0.37	-0.03	0.065	0.538
TrgLEV	35	0.26	0.25	0.15	166	0.18	0.19	0.13	**-0.083***	0.102
TrgINSTOWN	35	0.65	0.27	0.70	166	0.61	0.34	0.69	-0.044	0.811
TrgROA	35	0.03	0.18	0.03	166	0.06	0.13	0.05	0.033	0.488
TrgFAGE	35	2.37	0.92	2.48	166	2.41	0.98	2.56	0.041	0.629

Table 3, continued

	Actual mergers				Control mergers				T-test	Rank-sum test
Variable	N	Mean	SD	Median	N	Mean	SD	Median	dif. in mean	*p*-value
Motive = Enhance market position										
SimPROD	164	0.21	0.08	0.22	789	0.16	0.09	0.17	**-0.055*** **	**0.000**
GeoProx	164	-5.16	2.06	-5.48	789	-6.91	1.16	-7.04	**-1.747*** **	**0.000**
SimQ	164	-0.18	0.25	-0.07	789	-0.20	0.28	-0.07	-0.017	0.748
RELSIZE	164	0.34	0.33	0.26	789	0.36	0.38	0.23	0.025	0.878
TrgSIZE	164	7.50	1.53	7.50	789	7.45	1.57	7.47	-0.049	0.683
TrgQ	164	1.37	0.79	1.07	789	1.39	0.83	1.07	0.024	0.562
TrgRETURN	164	-0.01	0.36	-0.04	789	0.01	0.34	-0.02	0.019	0.239
TrgLEV	164	0.19	0.18	0.13	789	0.18	0.20	0.12	-0.004	0.264
TrgINSTOWN	164	0.61	0.30	0.68	789	0.57	0.31	0.58	**-0.046***	0.121
TrgROA	164	0.05	0.09	0.02	789	0.05	0.10	0.02	-0.007	0.515
TrgFAGE	164	2.36	0.92	2.48	789	2.43	0.95	2.64	0.061	0.328
Motive = Enrich product portfolios										
SimPROD	142	0.14	0.07	0.15	665	0.07	0.06	0.06	**-0.073*** **	**0.000**
GeoProx	142	-6.13	2.32	-7.04	665	-6.90	1.43	-7.21	**-0.778*** **	**0.004**
SimQ	142	-0.41	0.32	-0.35	665	-0.45	0.36	-0.35	-0.043	0.299
RELSIZE	142	0.23	0.26	0.13	665	0.22	0.29	0.11	-0.009	0.245
TrgSIZE	142	6.49	1.71	6.25	665	6.36	1.67	6.32	-0.124	0.528
TrgQ	142	2.24	1.38	1.78	665	2.13	1.29	1.75	-0.112	0.346
TrgRETURN	142	0.05	0.47	-0.03	665	0.01	0.42	-0.03	-0.04	0.688
TrgLEV	142	0.19	0.23	0.10	665	0.18	0.20	0.12	-0.014	0.754
TrgINSTOWN	142	0.80	0.24	0.88	665	0.70	0.29	0.78	**-0.095*** **	**0.000**
TrgROA	142	0.08	0.14	0.11	665	0.07	0.18	0.10	-0.019	0.325
TrgFAGE	142	2.34	1.04	2.64	665	2.55	1.01	2.77	**0.206** **	**0.026**
Motive = Expand into new geographic markets										
SimPROD	80	0.23	0.06	0.23	367	0.19	0.08	0.21	**-0.046*** **	**0.000**
GeoProx	80	-5.50	1.22	-5.60	367	-6.78	0.96	-6.75	**-1.278*** **	**0.000**
SimQ	80	-0.12	0.20	-0.04	367	-0.11	0.19	-0.05	0.003	0.160
RELSIZE	80	0.22	0.25	0.14	367	0.24	0.28	0.15	0.025	0.655
TrgSIZE	80	7.17	1.25	7.00	367	7.12	1.26	6.92	-0.05	0.645
TrgQ	80	1.15	0.40	1.02	367	1.15	0.43	1.03	0.001	0.791
TrgRETURN	80	0.01	0.40	-0.05	367	-0.05	0.32	-0.08	-0.061	0.336
TrgLEV	80	0.14	0.14	0.11	367	0.15	0.18	0.09	0.006	0.483
TrgINSTOWN	80	0.41	0.28	0.35	367	0.39	0.28	0.33	-0.021	0.494
TrgROA	80	0.04	0.06	0.02	367	0.04	0.06	0.02	-0.005	0.342
TrgFAGE	80	2.51	0.76	2.56	367	2.27	0.95	2.40	**-0.248** **	**0.053**
Motive = Acquire innovation resources										
SimPROD	38	0.17	0.06	0.16	173	0.09	0.07	0.08	**-0.073*** **	**0.000**
GeoProx	38	-6.63	2.02	-7.32	173	-6.89	1.67	-7.36	-0.257	0.586
SimQ	38	-0.54	0.40	-0.42	173	-0.48	0.36	-0.42	0.057	0.526
RELSIZE	38	0.12	0.28	0.03	173	0.15	0.38	0.02	0.028	0.479
TrgSIZE	38	5.10	1.25	5.07	173	5.22	1.18	5.15	0.116	0.635
TrgQ	38	3.43	1.88	2.90	173	2.86	1.53	2.54	**-0.578** **	**0.098**
TrgRETURN	38	0.07	0.65	0.10	173	0.01	0.50	-0.04	-0.065	0.673
TrgLEV	38	0.10	0.17	0.03	173	0.16	0.22	0.05	0.054	0.276
TrgINSTOWN	38	0.68	0.28	0.72	173	0.63	0.31	0.65	-0.055	0.337
TrgROA	38	-0.20	0.28	-0.19	173	-0.04	0.28	0.06	**0.167*** **	**0.000**
TrgFAGE	38	2.01	0.95	2.20	173	2.31	0.99	2.48	**0.302***	**0.046**

Table 3, continued

Panel B: Summary statistics and Pearson correlation matrices by subsamples driven by distinct value-creation motives

Variable	N	Mean	SD	Deal	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Motive = Improve cost efficiency														
(1) SimPROD	201	0.12	0.09	0.28***	1.00									
(2) GeoProx	201	-6.82	1.75	0.37***	0.14*	1.00								
(3) SimQ	201	-0.37	0.37	-0.01	0.37***	0.06	1.00							
(4) RELSIZE	201	0.28	0.32	-0.04	0.24***	0.16*	0.35***	1.00						
(5) TrgSIZE	201	6.47	1.52	0.07	0.08	0.06	0.12	0.25***	1.00					
(6) TrgQ	201	1.75	1.09	0.01	-0.29***	0.02	-0.27***	-0.07	-0.16*	1.00				
(7) TrgRETURN	201	-0.01	0.36	-0.07	-0.07	-0.08	0.02	0.10	0.16*	0.12	1.00			
(8) TrgLEV	201	0.19	0.20	0.15*	-0.10	0.10	-0.07	-0.07	0.40***	-0.01	0.11	1.00		
(9) TrgINSTOWN	201	0.62	0.33	0.05	-0.45***	-0.03	-0.25***	-0.07	0.29***	0.31***	0.10	0.21**	1.00	
(10) TrgROA	201	0.05	0.14	-0.09	-0.25***	0.01	-0.04	0.07	0.31***	0.04	0.28***	0.09	0.26***	1.00
(11) TrgFAGE	201	2.41	0.97	-0.02	-0.20**	0.00	-0.02	0.03	0.30***	-0.01	0.17*	0.20**	0.25***	0.23**
Motive = Enhance market position														
(1) SimPROD	953	0.17	0.09	0.23***	1.00									
(2) GeoProx	953	-6.61	1.51	0.44***	0.18***	1.00								
(3) SimQ	953	-0.20	0.28	0.02	0.46***	0.04	1.00							
(4) RELSIZE	953	0.36	0.37	-0.03	-0.04	-0.02	-0.08*	1.00						
(5) TrgSIZE	953	7.46	1.57	0.01	0.28***	0.05	0.26***	0.24***	1.00					
(6) TrgQ	953	1.39	0.82	-0.01	-0.34***	-0.09**	-0.55***	0.10**	-0.38***	1.00				
(7) TrgRETURN	953	0.00	0.35	-0.02	0.02	-0.05	-0.03	0.04	-0.05	0.08**	1.00			
(8) TrgLEV	953	0.18	0.19	0.01	-0.25***	-0.03	-0.16***	0.10**	0.12***	0.02	-0.10**	1.00		
(9) TrgINSTOWN	953	0.58	0.31	0.06	-0.28***	-0.06	-0.27***	0.27***	0.36***	0.18***	0.02	0.23***	1.00	
(10) TrgROA	953	0.05	0.10	0.03	-0.21***	0.02	-0.04	0.14***	0.18***	-0.12***	-0.02	0.26***	0.33***	1.00
(11) TrgFAGE	953	2.42	0.94	-0.02	-0.06	0.05	0.01	0.06	0.24***	-0.06	-0.00	-0.03	0.17***	0.10**
Motive = Enrich product portfolios														
(1) SimPROD	807	0.08	0.07	0.40***	1.00									
(2) GeoProx	807	-6.77	1.65	0.18***	0.17***	1.00								
(3) SimQ	807	-0.44	0.35	0.05	0.13***	0.06	1.00							
(4) RELSIZE	807	0.22	0.29	0.01	0.09**	0.04	0.08*	1.00						
(5) TrgSIZE	807	6.38	1.68	0.03	0.14***	0.10**	0.26***	0.31***	1.00					
(6) TrgQ	807	2.15	1.31	0.03	-0.02	0.04	-0.28***	0.09**	-0.19***	1.00				
(7) TrgRETURN	807	0.02	0.43	0.04	0.01	-0.00	-0.03	0.01	-0.01	0.07*	1.00			
(8) TrgLEV	807	0.18	0.20	0.03	0.01	0.04	0.10**	0.12***	0.41***	-0.05	-0.02	1.00		
(9) TrgINSTOWN	807	0.72	0.28	0.13***	0.04	0.05	0.13***	0.12***	0.50***	-0.02	0.08*	0.13***	1.00	
(10) TrgROA	807	0.07	0.17	0.04	-0.11**	0.08*	0.09*	0.13***	0.40***	-0.10**	0.06	0.14***	0.31***	1.00
(11) TrgFAGE	807	2.51	1.02	-0.08*	-0.13***	0.01	0.07*	0.10**	0.20***	-0.14***	0.00	0.00	0.08*	0.24***

Table 3, continued

Variable	N	Mean	SD	Deal	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Motive = Expand into new geographic markets														
(1) SimPROD	447	0.20	0.08	0.21***	1.00									
(2) GeoProx	447	-6.55	1.13	0.44***	0.28***	1.00								
(3) SimQ	447	-0.11	0.19	-0.01	0.40***	0.14**	1.00							
(4) RELSIZE	447	0.24	0.28	-0.03	0.03	-0.10*	-0.05	1.00						
(5) TrgSIZE	447	7.13	1.25	0.02	0.26***	-0.01	0.29***	0.28***	1.00					
(6) TrgQ	447	1.15	0.42	-0.00	-0.33***	-0.06	-0.67***	0.14**	-0.21***	1.00				
(7) TrgRETURN	447	-0.04	0.33	0.07	0.03	-0.08	-0.09	0.16***	0.00	0.04	1.00			
(8) TrgLEV	447	0.15	0.17	-0.01	-0.25***	-0.08	-0.12*	0.15**	0.31***	0.10*	0.01	1.00		
(9) TrgINSTOWN	447	0.39	0.28	0.03	-0.23***	-0.19***	-0.18***	0.26***	0.42***	0.24***	0.03	0.33***	1.00	
(10) TrgROA	447	0.04	0.06	0.03	-0.38***	-0.15**	-0.27***	0.11*	-0.04	0.29***	0.05	0.30***	0.38***	1.00
(11) TrgFAGE	447	2.31	0.92	0.10*	-0.09	0.00	-0.03	0.00	0.12**	0.04	0.11*	-0.00	0.17***	0.16***
Motive = Acquire innovation resources														
(1) SimPROD	211	0.11	0.07	0.39***	1.00									
(2) GeoProx	211	-6.84	1.74	0.06	0.28***	1.00								
(3) SimQ	211	-0.49	0.36	-0.06	-0.18**	0.05	1.00							
(4) RELSIZE	211	0.15	0.36	-0.03	0.12	0.01	0.06	1.00						
(5) TrgSIZE	211	5.20	1.19	-0.04	0.11	0.17*	0.01	0.17*	1.00					
(6) TrgQ	211	2.96	1.61	0.14*	0.34***	0.09	-0.47***	-0.06	0.07	1.00				
(7) TrgRETURN	211	0.02	0.53	0.05	-0.02	-0.08	0.01	0.15*	0.24***	0.10	1.00			
(8) TrgLEV	211	0.15	0.21	-0.10	0.08	0.03	-0.11	0.02	0.19**	0.12	-0.08	1.00		
(9) TrgINSTOWN	211	0.64	0.30	0.07	0.25***	0.08	0.03	0.15*	0.71***	0.27***	0.28***	0.09	1.00	
(10) TrgROA	211	-0.07	0.29	-0.22**	-0.51***	-0.09	0.19**	-0.05	0.24***	-0.30***	0.17*	-0.21**	0.11	1.00
(11) TrgFAGE	211	2.26	0.99	-0.12	-0.31***	-0.02	-0.07	0.02	0.11	-0.10	0.07	0.09	0.04	0.34***

Table 4: Results of Testing H1a and H1b

Table 4, Panel A, reports coefficient estimates from Model (1), which analyzes the effect of product similarity on the likelihood of mergers driven by operating synergies, using 459 matched groups of actual and control mergers. Model (1) is a conditional logit model with fixed effects at the matched actual-control merger group level, specified as follows. Control mergers are constructed by pairing each actual acquirer with up to five control target firms.

$$Deal = \gamma SimPROD + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgRETURN + \beta_4 TrgLEV + \beta_5 TrgINSTOWN + \beta_6 TrgFAGE + GroupFE \quad (1)$$

SimPROD is a proxy for product similarity, measured as the cosine similarity of two firms' word usages in business descriptions, developed by Phillips and Hoberg (2010; 2016). ***RELSIZE*** is a proxy for the relative size of the target firm to the acquirer, measured as the market capitalization of the (control) target firm relative to that of the acquirer. Several control variables are included to account for target firm characteristics: ***TrgSIZE***, the natural logarithm of the book value of total assets; ***TrgRETURN***, the 12-month buy-and-hold cumulative abnormal return relative to the CRSP market index, measured over 12 months ending at two months prior to the merger announcement; ***TrgLEV***, the financial leverage ratio, calculated as the sum of current and long-term debt scaled by total assets; ***TrgINSTOWN***, the percentage of institutional ownership; and ***TrgFAGE***, firm age, calculated as the natural logarithm of the number of years since the firm's first appearance in the CRSP monthly data.

Columns in **Panel A** report coefficient estimates from Model (1) across different estimation samples: column (1) presents results based on the pooled sample of operating synergy-driven mergers; columns (2) through (6) present results for subsamples categorized by distinct value-creation motives, including (2) improving cost efficiency, (3) enhancing market position, (4) enriching product portfolios, (5) geographic market expansion, and (6) acquiring innovation resources.

Panel B reports *p*-values from Wald tests assessing whether the coefficients on ***SimPROD*** across subgroup analyses from Panel A, columns (2) through (6), differ significantly from one another; that is, whether their confidence intervals do not overlap. For example, the test comparing the coefficient of ***SimPROD*** in column (2) with that in column (3) yields a *p*-value of 0.192, suggesting no statistically significant difference. This indicates that the effect of product similarity on merger likelihood is statistically equivalent between mergers aimed at improving cost efficiency and those aimed at enhancing market position.

All continuous variables are winsorized at the 1st and 99th percentiles based on the pooled sample. Variables are then standardized by subtracting the mean and dividing by the standard deviation of the estimation sample in each analysis. Standard errors are clustered at the matched actual-control merger group level, and *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4, continued

Panel A: Coefficient estimates from the conditional logit model–Model (1)–across value-creation contexts

	Pred. sign	(Pooled sample)	(Cost efficiency)	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
		(1)	(2)	(3)	(4)	(5)	(6)
SimPROD	+	**2.34*** **	**3.04*** **	**2.00*** **	**1.99*** **	**1.75*** **	**2.77*** **
		(15.23)	**(3.93)**	**(8.71)**	**(8.42)**	**(5.29)**	**(5.15)**
RelSIZE	–	-0.50***	-0.52	-0.64***	-0.12	-0.39	-0.53
		(-3.93)	(-1.24)	(-3.23)	(-0.70)	(-1.36)	(-1.26)
TrgSIZE	?	0.50*	2.20***	0.67	-0.11	0.18	-0.10
		(1.72)	(2.70)	(1.34)	(-0.22)	(0.36)	(-0.10)
TrgRETURN	–/?	0.05	-0.25	-0.13	0.11	0.29*	0.36
		(0.66)	(-1.11)	(-0.93)	(0.79)	(1.89)	(1.23)
TrgLEV	?	-0.02	0.42	-0.00	-0.05	0.06	-0.33
		(-0.26)	(1.35)	(-0.02)	(-0.27)	(0.39)	(-0.99)
TrgInstOwn	+	0.60***	0.67**	0.58***	0.89***	0.22	0.61
		(5.51)	(2.09)	(2.93)	(4.64)	(1.07)	(1.45)
TrgFAGE	?	-0.01	0.06	0.04	-0.25**	0.41***	-0.30
		(-0.22)	(0.19)	(0.43)	(-2.07)	(2.67)	(-1.20)
N of Obs.		2,619	201	953	807	447	211
N of Groups		459	35	164	142	80	38
Group FE		Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2		0.33	0.49	0.27	0.45	0.24	0.52
Model test *p*-value		0.00	0.00	0.00	0.00	0.00	0.00
Link Test							
p-value of _hat		0.000	0.000	0.000	0.000	0.000	0.001
p-value of _hatsq		0.000	0.169	0.017	0.231	0.047	0.078

Panel B: Wald tests of pairwise differences in the coefficients on *SimPROD* across subgroup analyses

Wald test *p*-values are reported.	(Market position) (3)	(Product portfolio) (4)	(Geo expansion) (5)	(Innovation resources) (6)
(2) Cost efficiency	0.192	0.188	0.122	0.768
(3) Market position		0.974	0.535	0.185
(4) Product portfolio			0.557	0.181
(5) Geo expansion				0.105

Table 5: Results of Testing H2a and H2b

Table 5, Panel A, presents coefficient estimates from Model (2), which analyzes the effect of geographic proximity on the likelihood of mergers motivated by operating synergies, using 459 matched groups of actual and control mergers. Model (2) is a conditional logit model with fixed effects at the matched actual-control merger group level, specified as follows. Control mergers are constructed by pairing each actual acquirer with up to five control target firms.

$$Deal = \gamma GeoProx + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgRETURN + \beta_4 TrgLEV + \beta_5 TrgINSTOWN + \beta_6 TrgFAGE + GroupFE \quad (2)$$

The dependent variable (***Deal***) equals one if the observation refers to an actual merger and zero otherwise. ***GeoProx*** is a proxy for geographic proximity, calculated as the negative natural logarithm of one plus the geographic distance between firms. ***RELSIZE*** is a proxy for the relative size of the target firm to the acquirer, measured as the market capitalization of the (control) target firm relative to that of the acquirer. Several control variables are included to account for target firm characteristics: ***TrgSIZE***, the natural logarithm of the book value of total assets; ***TrgRETURN***, the 12-month buy-and-hold cumulative abnormal return relative to the CRSP market index, measured over 12 months ending at two months prior to the merger announcement; ***TrgLEV***, the financial leverage ratio, calculated as the sum of current and long-term debt scaled by total assets; ***TrgINSTOWN***, the percentage of institutional ownership; and ***TrgFAGE***, firm age, calculated as the natural logarithm of the number of years since the firm's first appearance in the CRSP monthly data.

Columns in **Panel A** report coefficient estimates from Model (2) across different estimation samples: column (1) presents results based on the pooled sample of operating synergy-driven mergers; columns (2) through (6) present results for subsamples categorized by distinct value-creation motives, including (2) improving cost efficiency, (3) enhancing market position, (4) enriching product portfolios, (5) geographic market expansion, and (6) acquiring innovation resources.

Panel B reports *p*-values from Wald tests assessing whether the coefficients on ***GeoProx*** across subgroup analyses from Panel A, columns (2) through (6), differ significantly from one another; that is, whether their confidence intervals do not overlap. For instance, the test comparing the coefficient of ***GeoProx*** in column (3) with that in column (4) yields a *p*-value of 0.000, indicating a statistically significant difference at the 1% level. This suggests that the effect of geographic proximity on merger likelihood is significantly stronger in mergers aimed at enhancing market position than in mergers motivated by enriching product portfolios.

All continuous variables are winsorized at the 1st and 99th percentiles based on the pooled sample. Variables are then standardized by subtracting the mean and dividing by the standard deviation of the estimation sample in each analysis. Standard errors are clustered at the matched actual-control merger group level, and *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5, continued

Panel A: Coefficient estimates for the conditional logit model–Model (2)–across value-creation contexts

	Pred. sign	(Pooled sample) (1)	(Cost efficiency) (2)	(Market position) (3)	(Product portfolio) (4)	(Geo expansion) (5)	(Innovation resources) (6)
GeoProx	+	**0.78*** **	**0.79*** **	**1.16*** **	**0.48*** **	**1.47*** **	0.20
		(11.61)	**(2.96)**	**(8.24)**	**(4.92)**	**(5.04)**	(0.95)
RelSIZE	–	-0.41***	-0.85*	-0.39**	-0.16	-0.48	-0.55
		(-4.00)	(-1.95)	(-2.02)	(-1.52)	(-1.09)	(-1.48)
TrgSIZE	?	0.83***	2.40**	1.03**	0.26	1.13*	-0.34
		(3.67)	(2.38)	(2.15)	(0.75)	(1.67)	(-0.55)
TrgRETURN	–/?	0.06	-0.31	-0.07	0.10	0.40**	0.19
		(0.84)	(-1.28)	(-0.44)	(0.81)	(1.97)	(0.90)
TrgLEV	?	-0.06	0.14	-0.13	0.01	-0.32	-0.25
		(-0.78)	(0.33)	(-0.90)	(0.11)	(-1.08)	(-1.01)
TrgInstOwn	+	0.65***	0.68	0.56***	0.87***	0.33	0.85**
		(6.86)	(1.63)	(2.93)	(5.87)	(1.43)	(2.09)
TrgFAGE	?	-0.14**	-0.12	-0.17	-0.30***	0.33*	-0.41**
		(-2.31)	(-0.48)	(-1.52)	(-2.82)	(1.92)	(-2.30)
N of Obs.		2,619	201	953	807	447	211
N of Groups		459	35	164	142	80	38
Group FE		Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2		0.18	0.30	0.30	0.13	0.39	0.11
Model test *p*-value		0.00	0.01	0.00	0.00	0.00	0.00
Link Test							
p-value of _hat		0.000	0.000	0.000	0.000	0.000	0.001
p-value of _hatsq		0.183	0.943	0.738	0.726	0.009	0.378

Panel B: Wald tests of pairwise differences in the coefficients on *GeoProx* across subgroup analyses

Wald test *p*-values are reported.	(Market position) (3)	(Product portfolio) (4)	(Geo expansion) (5)	(Innovation resources) (6)
(2) Cost efficiency	0.323	0.222	**0.085**	**0.060**
(3) Market position		**0.000**	0.225	**0.000**
(4) Product portfolio			**0.001**	0.194
(5) Geo expansion				**0.000**

Table 6: Results of Testing H3a and H3b

Table 6, Panel A, presents coefficient estimates from Model (3), which analyzes the effect of resource quality similarity on the likelihood of operating synergy-driven mergers, using 459 matched groups of actual and control mergers. Model (3) is a conditional logit model with fixed effects at the matched actual-control merger group level, specified as follows. Control mergers are constructed by pairing each actual acquirer with up to five control target firms.

$$Deal = \gamma SimQ + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgQ + \beta_4 TrgRETURN + \beta_5 TrgLEV + \beta_6 TrgINSTOWN + \beta_7 TrgROA + \beta_8 TrgFAGE + GroupFE \quad (3)$$

The dependent variable (***Deal***) equals one if the observation refers to an actual merger and zero otherwise. ***SimQ*** is a proxy for resource quality similarity, measured as the negative absolute difference in the natural logarithm of Tobin's Q. ***RELSIZE*** is a proxy for the relative size of the target firm to the acquirer, measured as the market capitalization of the (control) target firm relative to that of the acquirer. Several control variables are included to account for target firm characteristics: ***TrgSIZE***, the natural logarithm of the book value of total assets; ***TrgQ***, the market-to-book value of total assets; ***TrgRETURN***, the 12-month buy-and-hold cumulative abnormal return relative to the CRSP market index, measured over 12 months ending at two months prior to the merger announcement; ***TrgLEV***, the financial leverage ratio, calculated as the sum of current and long-term debt scaled by total assets; ***TrgINSTOWN***, the percentage of institutional ownership; ***TrgROA***, return on assets, measured as operating income before depreciation scaled by total assets; and ***TrgFAGE***, firm age, calculated as the natural logarithm of the number of years since the firm's first appearance in the CRSP monthly data.

Columns in **Panel A** report coefficient estimates from Model (3) based on different estimation samples: column (1) presents results based on the pooled sample of operating synergy-driven mergers; columns (2) through (6) present results for subsamples categorized by distinct value-creation motives, including (2) improving cost efficiency, (3) enhancing market position, (4) enriching product portfolios, (5) geographic market expansion, and (6) acquiring innovation resources.

Panel B presents *p*-values from Wald tests assessing whether the coefficients on ***SimQ*** across subgroup analyses from Panel A, columns (2) through (6), differ significantly from one another; that is, whether their confidence intervals do not overlap. For instance, the test comparing the coefficient of ***SimQ*** in column (2) with that in column (3) yields a *p*-value of 0.914, indicating no statistically significant difference. This suggests that the effect of similarity in Tobin's Q on merger likelihood is statistically equivalent between mergers aimed at improving cost efficiency and those aimed at enhancing market position.

All continuous variables are winsorized at the 1st and 99th percentiles based on the pooled sample. Variables are then standardized by subtracting the mean and dividing by the standard deviation of the estimation sample in each analysis. Standard errors are clustered at the matched actual-control merger group level, and *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6, continued

Panel A: Coefficient estimates for the conditional logit model–Model (3)–across value-creation contexts

	Pred. sign	(Pooled sample)	(Cost efficiency)	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
		(1)	(2)	(3)	(4)	(5)	(6)
SimQ	+	**0.22*****	0.22	**0.18***	**0.29****	-0.01	**0.56****
		(2.99)	(0.67)	**(1.68)**	**(2.52)**	(-0.06)	**(2.10)**
RelSIZE	–	-0.60***	-1.08***	-0.61***	-0.30**	-0.62**	-0.95**
		(-5.69)	(-2.60)	(-3.49)	(-2.09)	(-2.12)	(-2.11)
TrgSIZE	?	1.14***	3.34***	1.32***	0.29	0.80*	0.98
		(4.82)	(3.11)	(3.20)	(0.77)	(1.75)	(1.52)
TrgQ	?	0.38***	0.47	0.19	0.26*	-0.09	0.87**
		(4.41)	(1.43)	(1.57)	(1.75)	(-0.54)	(2.22)
TrgRETURN	–/?	0.01	-0.32	-0.15	0.07	0.17	0.18
		(0.18)	(-1.42)	(-1.27)	(0.64)	(1.17)	(0.79)
TrgLEV	?	-0.09	0.24	-0.12	-0.06	-0.22	-0.47
		(-1.44)	(0.80)	(-1.20)	(-0.47)	(-1.52)	(-1.58)
TrgInstOwn	+	0.54***	0.82	0.44***	0.79***	0.19	0.68*
		(6.37)	(1.57)	(3.22)	(5.70)	(1.01)	(1.88)
TrgROA	–	-0.10	-0.49**	0.18	0.20*	0.15	-0.99***
		(-1.56)	(-2.00)	(1.44)	(1.72)	(0.82)	(-3.01)
TrgFAGE	?	-0.09	-0.19	-0.09	-0.34***	0.32**	-0.30
		(-1.63)	(-0.79)	(-0.98)	(-3.21)	(2.10)	(-1.44)
N of Obs.		2,619	201	953	807	447	211
N of Groups		459	35	164	142	80	38
Group FE		Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2		0.05	0.21	0.04	0.09	0.05	0.25
Model test *p*-value		0.00	0.14	0.00	0.00	0.06	0.00
Link Test							
p-value of _hat		0.000	0.000	0.000	0.000	0.000	0.000
p-value of _hatsq		0.538	0.530	0.779	0.741	0.861	0.714

Panel B: Wald tests of pairwise differences in the coefficients on *SimQ* across subgroup analyses

Wald test *p*-values are reported.	(Market position) (3)	(Product portfolio) (4)	(Geo expansion) (5)	(Innovation resources) (6)
(2) Cost efficiency	0.914	0.839	0.528	0.430
(3) Market position		0.497	0.314	0.191
(4) Product portfolio			0.123	0.359
(5) Geo expansion				**0.065**

Additional Analyses

Table 7: Shareholder Wealth Outcomes

Table 7, Panel A, presents summary statistics and Pearson correlations for variables included in Model (4), based on a sample of 452 operating synergy-driven mergers for shareholder wealth effect analyses. Model (4) is an ordinary least squares (OLS) regression model evaluating the effect of each interfirm similarity proxy on shareholder wealth outcomes. Fixed effects for the acquirer industry and merger announcement year are included. Model (4) is specified as follows, where *Similarity* denotes ***SimPROD***, ***GeoProx***, or ***SimQ***.

$$\begin{aligned} DV = {} & \alpha + \gamma Similarity + \beta_1 Cash + \beta_2 Stock + \beta_3 Compete + \beta_4 Toehold + \beta_5 Tender + \beta_6 RelDealSize \\ & + \beta_7 AcqME + \beta_8 AcqRETURN + \beta_9 AcqLEV + \beta_{10} AccqINSTOWN + \beta_{11} AcqFAGE + \beta_{12} TrgME \\ & + \beta_{13} TrgRETURN + \beta_{14} TrgLEV + \beta_{15} TrgINSTOWN + \beta_{16} TrgFAGE + AcqIndFE + YearFE + \varepsilon \end{aligned} \quad (4)$$

The dependent variable (***DV***) is one of the six shareholder wealth outcome measures, including the expected merger synergy (***CGAIN***), the acquirer's cumulative abnormal dollar gains (***AGAIN***) and percentage returns (***ACAR***), the target's bargaining power relative to the acquirer (***RELTGAIN***), and the target's cumulative abnormal percentage returns (***TCAR***) and dollar gains (***TGAIN***). Details on the computation of these outcome variables are provided in Appendix A. ***SimPROD*** is a proxy for product similarity, measured as the cosine similarity of two firms' word usages in business descriptions, developed by Phillips and Hoberg (2010; 2016). ***GeoProx*** is a proxy for geographic proximity, calculated as the negative natural logarithm of one plus the geographic distance between firms. ***SimQ*** is a proxy for resource quality similarity, measured as the negative absolute difference in the natural logarithm of Tobin's Q. ***Cash*** is an indicator variable equal to one if the payment is made entirely by cash; zero otherwise. ***Stock*** is an indicator variable equal to one if the payment is made entirely by equity; zero otherwise. ***Compete*** is an indicator variable equal to one if the target firm received multiple competing bids; zero otherwise. ***Toehold*** is an indicator variable equal to one if the acquirer holds a positive percentage of the target's common shares preceding the merger announcement. ***Tender*** is an indicator variable equal to one if the merger is executed through a tender offer; zero otherwise. ***RelDealSize*** is a proxy for the relative size of the deal value to the acquirer's pre-merger market capitalization. Firm-level controls are included for both acquirers and target firms. Prefixes ***Acq*** and ***Trg*** denote acquirer and target firm variables, respectively. ***ME*** is a proxy for firm size, measured as the natural logarithm of market capitalization as of the fiscal year-end prior to the merger announcement. ***RETURN*** denotes the 12-month buy-and-hold cumulative abnormal return relative to the CRSP market index, measured over 12 months ending at two months prior to the merger announcement. ***LEV*** denotes the financial leverage ratio, calculated as the sum of current and long-term debt scaled by total assets. ***INSTOWN*** is the percentage of institutional ownership. ***FAGE*** represents firm age, calculated as the natural logarithm of the number of years since the firm's first appearance in the CRSP monthly data.

Panel B presents coefficient estimates from Model (4). Each row corresponds to one similarity measure: ***SimPROD***, ***GeoProx***, or ***SimQ***. The six columns represent distinct measures of shareholder wealth outcomes. Each cell represents a coefficient estimate from a regression model. To illustrate, the cell at row (a) and column (1) reports the coefficient estimate for ***SimPROD*** from the regression where the dependent variable (***DV***) is ***CGAIN,*** and the similarity measure (***Similarity***) is ***SimPROD***.

The estimation samples for rows (a)–(c) comprise the pooled sample of 452 operating synergy-driven mergers, excluding two deals with missing shareholder wealth outcome data, four deals in which the acquirer announced two deals on the same day, and one hostile takeover from the sample of 459 deals used in the target selection analyses. Rows (d)–(f) restrict the sample further to deals with absolute ***AGAIN*** values less than $1 billion. Rows (g)–(i) apply an additional restriction, limiting to deals with absolute ***AGAIN*** values less than $500. All continuous variables are winsorized at the 1st and 99th percentiles based on the sample of 452 mergers. Variables are then standardized by subtracting the mean and dividing by the standard deviation within each estimation sample. Standard errors are two-way clustered by acquirer industry and merger announcement year, and *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7, continued

Panel A: Summary statistics and Pearson correlation coefficients of all variables used in Model (4)

	Summary statistics			Pearson correlation coefficients								
Variables	N	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) CGAIN	452	190.46	1507.43	1.00								
(2) AGAIN	452	-137.08	1421.40	0.79***	1.00							
(3) ACAR	452	-0.01	0.06	0.36***	0.40***	1.00						
(4) RELTGAIN	452	0.04	0.06	-0.25***	-0.36***	-0.66***	1.00					
(5) TCAR	452	0.27	0.26	0.21***	0.10*	0.12*	0.10*	1.00				
(6) TGAIN	452	320.93	811.78	0.28***	-0.30***	-0.04	0.17***	0.18***	1.00			
(7) SimPROD	452	0.19	0.08	-0.03	0.04	-0.02	0.05	-0.21***	-0.16***	1.00		
(8) GeoProx	452	-5.66	2.13	-0.09	-0.09	-0.06	0.10*	-0.10*	-0.00	0.24***	1.00	
(9) SimQ	452	-0.28	0.32	-0.04	0.05	-0.05	0.07	-0.21***	-0.16***	0.39***	0.22***	1.00
(10) Cash	452	0.34	0.47	0.17***	0.10*	0.19***	-0.18***	0.34***	0.12*	-0.36***	-0.21***	-0.32***
(11) Stock	452	0.28	0.45	-0.11*	-0.03	-0.15**	0.07	-0.20***	-0.14**	0.33***	0.19***	0.21***
(12) Compete	452	0.03	0.17	-0.03	-0.04	-0.03	0.01	-0.10*	0.01	-0.03	-0.02	-0.03
(13) Toehold	452	0.01	0.10	-0.07	-0.04	-0.05	0.03	-0.04	-0.04	-0.03	-0.08	-0.12**
(14) Tender	452	0.17	0.37	0.12*	0.03	0.10*	-0.09	0.21***	0.17***	-0.24***	-0.21***	-0.33***
(15) RelDealSize	452	0.35	0.39	-0.08	-0.08	-0.10*	0.25***	-0.32***	-0.02	0.21***	0.14**	0.11*
(16) AcqME	452	22466.28	48565.52	0.18***	-0.10*	0.02	-0.14**	0.21***	0.50***	-0.28***	-0.11*	-0.22***
(17) AcqRETURN	452	0.06	0.28	-0.04	-0.05	-0.05	0.05	-0.04	0.03	-0.01	-0.03	-0.05
(18) AcqLEV	452	0.19	0.16	0.04	-0.04	0.10*	-0.05	0.04	0.15**	-0.25***	-0.14**	-0.24***
(19) AcqInstOwn	452	0.73	0.22	0.09	0.04	0.08	-0.08	0.03	0.09	-0.26***	-0.17***	-0.20***
(20) AcqFAGE	452	2.92	0.94	0.10*	-0.05	-0.04	-0.06	0.11*	0.25***	-0.22***	-0.06	-0.01
(21) TrgME	452	1892.77	4053.77	-0.12*	-0.48***	-0.17***	0.09*	-0.18***	0.62***	-0.13**	0.02	-0.12*
(22) TrgRETURN	452	0.03	0.47	0.13**	0.09	0.03	-0.04	-0.08	0.09	-0.02	-0.11*	-0.05
(23) TrgLEV	452	0.18	0.20	0.02	-0.07	0.06	-0.07	-0.04	0.13**	-0.08	-0.02	-0.17***
(24) TrgInstOwn	452	0.65	0.30	0.10*	-0.05	0.00	-0.01	-0.16***	0.27***	-0.34***	-0.18***	-0.28***
(25) TrgFAGE	452	2.36	0.93	0.01	-0.07	0.03	0.04	-0.00	0.16***	-0.12*	0.06	0.10*

Table 7, continued

Panel B: Coefficient estimates from Model (4), reporting the effects of product similarity (*SimPROD*), geographic proximity (*GeoProx*), and resource quality similarity (*SimQ*) on shareholder wealth outcomes, estimated in separate regressions for each similarity proxy and outcome variable.

		(CGAIN)	(AGAIN)	(ACAR)	(RELTGAIN)	(TCAR)	(TGAIN)
		(1)	(2)	(3)	(4)	(5)	(6)
	Pooled sample mergers for shareholder wealth effect analyses						
(a)	SimPROD	0.15	**0.07***	**0.18*****	**-0.13***	-0.04	0.08
		(1.42)	**(1.85)**	**(5.02)**	**(-2.00)**	(-0.59)	(0.87)
(b)	GeoProx	-0.00	-0.04	0.02	0.02	-0.03	0.06
		(-0.09)	(-0.68)	(0.41)	(0.30)	(-0.59)	(1.57)
(c)	SimQ	**0.08***	**0.09***	0.10	-0.02	-0.09	-0.02
		(2.16)	**(2.05)**	(1.44)	(-0.25)	(-1.37)	(-0.53)
	Subsample excluding deals where AGAIN >= $1 billion						
(d)	SimPROD	0.04	0.11	**0.17*****	**-0.15***	-0.06	-0.03
		(0.39)	(1.41)	**(4.69)**	**(-2.02)**	(-0.73)	(-0.36)
(e)	GeoProx	0.01	0.01	-0.00	0.04	-0.01	0.00
		(0.22)	(0.17)	(-0.04)	(0.62)	(-0.12)	(0.05)
(f)	SimQ	0.06	0.11	0.07	0.03	-0.11	-0.02
		(0.86)	(1.18)	(1.14)	(0.45)	(-1.22)	(-0.25)
	Subsample excluding deals where AGAIN >= $500 million						
(g)	SimPROD	0.07	0.10	**0.15*****	-0.12	-0.06	0.03
		(0.80)	(1.16)	**(4.83)**	(-1.32)	(-0.62)	(0.31)
(h)	GeoProx	0.05	0.00	-0.00	0.06	-0.02	0.06
		(1.09)	(0.06)	(-0.06)	(0.86)	(-0.36)	(0.95)
(i)	SimQ	0.04	0.07	0.09	0.04	-0.12	-0.01
		(0.52)	(1.58)	(1.39)	(0.55)	(-1.12)	(-0.07)

Table 8: Shareholder Wealth Outcomes across Different Value-Creation Motives

Table 8, Panel A, presents summary statistics of shareholder wealth outcome measures and their Pearson correlations with three interfirm similarity proxies by subsamples categorized by distinct value-creation motives.

Panel B presents coefficient estimates from ordinary least squares (OLS) regressions of Model (5), separately for product similarity (***SimPROD***), geographic proximity (***GeoProx***), and Tobin's Q similarity (***SimQ***). Each regression assesses the effect of a specific interfirm similarity proxy on a particular shareholder wealth outcome measure across distinct value-creation motive subgroups. Column titles denote specific shareholder wealth outcome measures. Model (5) is specified as follows, where *Similarity* denotes ***SimPROD***, ***GeoProx***, or ***SimQ***.

$$\begin{aligned} DV = \alpha + (&\gamma Similarity + \beta_1 Cash + \beta_2 Stock + \beta_3 Compete + \beta_4 Toehold + \beta_5 Tender + \beta_6 RelDealSize \\ &+ \beta_7 AcqME + \beta_8 AcqRETURN + \beta_9 AcqLEV + \beta_{10} AccqINSTOWN + \beta_{11} AcqFAGE + \beta_{12} TrgME \\ &+ \beta_{13} TrgRETURN + \beta_{14} TrgLEV + \beta_{15} TrgINSTOWN + \beta_{16} TrgFAGE) \times MotiveG \\ &+ AcqIndFE + YearFE + \varepsilon \end{aligned} \quad (5)$$

The dependent variable (***DV***) is one of the six shareholder wealth outcome measures, including the expected merger synergy (***CGAIN***), the acquirer's cumulative abnormal dollar gains (***AGAIN***) and percentage returns (***ACAR***), the target's bargaining power relative to the acquirer (***RELTGAIN***), and the target's cumulative abnormal percentage returns (***TCAR***) and dollar gains (***TGAIN***). Details on the computation of these outcome variables are provided in Appendix A. ***SimPROD*** is a proxy for product similarity, measured as the cosine similarity of two firms' word usages in business descriptions, developed by Phillips and Hoberg (2010; 2016). ***GeoProx*** is a proxy for geographic proximity, calculated as the negative natural logarithm of one plus the geographic distance between firms. ***SimQ*** is a proxy for resource quality similarity, measured as the negative absolute difference in the natural logarithm of Tobin's Q. ***Cash*** is an indicator variable equal to one if the payment is made entirely by cash; zero otherwise. ***Stock*** is an indicator variable equal to one if the payment is made entirely by equity; zero otherwise. ***Compete*** is an indicator variable equal to one if the target firm received multiple competing bids; zero otherwise. ***Toehold*** is an indicator variable equal to one if the acquirer holds a positive percentage of the target's common shares preceding the merger announcement; zero otherwise. ***Tender*** is an indicator variable equal to one if the merger is executed through a tender offer; zero otherwise. ***RelDealSize*** is a proxy for the relative size of the deal value to the acquirer's pre-merger market capitalization. Firm-level controls are included for both acquirers and target firms. Prefixes ***Acq*** and ***Trg*** denote acquirer and target firm variables, respectively. ***ME*** is a proxy for firm size, measured as the natural logarithm of market capitalization as of the fiscal year-end prior to the merger announcement. ***RETURN*** denotes the 12-month buy-and-hold cumulative abnormal return relative to the CRSP market index, measured over 12 months ending at two months prior to the merger announcement. ***LEV*** denotes the financial leverage ratio, calculated as the sum of current and long-term debt scaled by total assets. ***INSTOWN*** is the percentage of institutional ownership. ***FAGE*** represents firm age, calculated as the natural logarithm of the number of years since the firm's first appearance in the CRSP monthly data. ***MotiveG*** is a categorical variable with five value-creation motive subgroups: (1) improving cost efficiency (baseline subgroup), (2) enhancing market position (2.*MotiveG*), (3) enriching product portfolios (3.*MotiveG*), (4) expanding into new geographic areas (4.*MotiveG*), and (5) acquiring innovation resources (5.*MotiveG*).

Panel C reports only the statistically significant coefficient estimates for the similarity proxies within specific value-creation motive subgroups. Wald tests are conducted on linear combinations of the baseline coefficient and the interaction terms. For instance, the first cell shows that ***SimPROD*** is significantly and positively associated with ***CGAIN*** ($\gamma = 0.04$, p-value = 0.027) in mergers aimed at improving cost efficiency.

The estimation samples comprise 452 operating synergy-driven mergers for analyzing shareholder wealth effects. All continuous variables are winsorized at the 1st and 99th percentiles of the sample's range and then standardized by subtracting the sample mean and dividing by the sample standard deviation. Standard errors are two-way clustered by acquirer industry and merger announcement year, and t-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8, continued

Panel A: Summary statistics of shareholder wealth outcome measures and their Pearson correlations with three similarity proxies by distinct value-creation motives

	Summary statistics				Pearson correlation coefficients		
	N	Mean	SD	Median	SimPROD	GeoProx	SimQ
Motive = Improve cost efficiency							
CGAIN	31	8.15	1006.26	14.02	0.17	-0.08	-0.13
AGAIN	31	-124.03	886.32	-4.46	0.23	-0.02	-0.11
ACAR	31	-0.02	0.07	0.00	0.04	0.24	0.11
RELTGAIN	31	0.04	0.07	0.02	0.25	0.02	0.12
TCAR	31	0.25	0.26	0.22	0.07	-0.15	-0.11
TGAIN	31	132.18	272.77	64.74	-0.11	-0.22	-0.10
Motive = Enhance market position							
CGAIN	163	120.46	963.39	10.39	-0.11	-0.17*	-0.09
AGAIN	163	-122.93	943.08	-21.35	0.08	-0.15	0.08
ACAR	163	-0.02	0.06	-0.02	0.04	-0.13	-0.16*
RELTGAIN	163	0.05	0.06	0.05	-0.07	0.13	-0.01
TCAR	163	0.22	0.23	0.17	-0.26***	-0.00	-0.16*
TGAIN	163	240.66	629.93	59.04	-0.29***	-0.04	-0.24**
Motive = Enrich product portfolio							
CGAIN	142	113.21	1789.33	119.63	0.11	-0.03	0.22**
AGAIN	142	-354.60	1891.39	-3.57	0.02	-0.13	0.14
ACAR	142	-0.01	0.06	0.00	0.03	-0.08	0.13
RELTGAIN	142	0.03	0.06	0.02	0.09	0.09	0.02
TCAR	142	0.26	0.22	0.24	-0.08	0.01	-0.07
TGAIN	142	469.22	1053.61	149.08	0.05	0.20*	0.12
Motive = Expand into new geographic areas							
CGAIN	80	21.89	1119.76	14.41	-0.08	0.02	-0.21
AGAIN	80	-101.29	1130.68	-9.30	-0.01	0.13	-0.17
ACAR	80	-0.01	0.06	-0.01	-0.07	-0.02	-0.26*
RELTGAIN	80	0.03	0.05	0.03	0.00	0.03	0.26*
TCAR	80	0.26	0.24	0.21	-0.29**	-0.12	-0.19
TGAIN	80	107.25	242.66	28.53	-0.23*	-0.40***	-0.04
Motive = Acquire innovation resources							
CGAIN	36	1343.65	2622.86	88.76	-0.15	-0.04	-0.17
AGAIN	36	566.13	1800.56	14.23	-0.13	0.04	0.03
ACAR	36	0.00	0.05	0.00	-0.12	0.19	0.15
RELTGAIN	36	0.02	0.05	0.01	0.02	-0.16	-0.08
TCAR	36	0.52	0.40	0.48	-0.37*	-0.26	-0.22
TGAIN	36	736.78	1246.22	156.94	-0.06	-0.13	-0.44**

Table 8, continued

Panel B: Coefficient estimates for similarity proxies from Model (5), analyzing the effects of product similarity, geographic proximity, and Tobin's Q similarity on shareholder wealth outcomes across subgroups of mergers aimed at distinct value-creation motives, separately

		(CGAIN)	(AGAIN)	(ACAR)	(RELTGAIN)	(TCAR)	(TGAIN)
		(1)	(2)	(3)	(4)	(5)	(6)
(a)	Model (5): Similarity = SimPROD						
	(1) SimPROD	0.40**	0.48**	0.34*	-0.18	0.18	-0.09
		(2.49)	(2.29)	(2.06)	(-1.03)	(1.31)	(-0.90)
	(2) 2.MotiveG × SimPROD	-0.39*	-0.41*	-0.04	-0.11	-0.27	-0.01
		(-2.13)	(-1.99)	(-0.18)	(-0.58)	(-1.35)	(-0.12)
	(3) 3.MotiveG × SimPROD	0.02	-0.32	-0.09	0.10	-0.12	0.33
		(0.07)	(-1.71)	(-0.39)	(0.41)	(-0.50)	(1.36)
	(4) 4.MotiveG× SimPROD	-0.41**	-0.51**	-0.20	-0.02	-0.49**	0.12
		(-2.80)	(-2.67)	(-0.76)	(-0.13)	(-2.72)	(1.00)
	(5) 5.MotiveG × SimPROD	-1.30**	-0.93*	-0.56	0.06	-0.40	-0.68*
		(-2.50)	(-2.10)	(-1.23)	(0.15)	(-0.77)	(-2.10)
(b)	Model (5): Similarity = GeoProx						
	(1) GeoProx	-0.07	-0.10	0.14	0.04	0.02	0.03
		(-0.92)	(-1.36)	(1.66)	(0.25)	(0.16)	(0.80)
	(2) 2.MotiveG × GeoProx	-0.04	-0.04	-0.21	0.03	-0.00	-0.00
		(-0.25)	(-0.24)	(-1.23)	(0.13)	(-0.01)	(-0.01)
	(3) 3.MotiveG × GeoProx	0.12	0.11	-0.11	-0.03	-0.01	0.04
		(0.87)	(1.16)	(-1.08)	(-0.21)	(-0.04)	(0.61)
	(4) 4.MotiveG × GeoProx	0.09	0.10	-0.36	0.22	-0.40	0.01
		(0.59)	(0.58)	(-0.98)	(0.76)	(-1.36)	(0.06)
	(5) 5.MotiveG × GeoProx	0.10	0.25	-0.16	-0.21	0.01	-0.30
		(0.48)	(1.05)	(-0.91)	(-1.32)	(0.05)	(-1.27)
(c)	Model (5): Similarity = SimQ						
	(1) SimQ	0.16	0.07	0.39**	-0.28	0.13	0.14**
		(1.00)	(0.47)	(2.68)	(-1.36)	(1.00)	(2.25)
	(2) 2.MotiveG × SimQ	-0.10	-0.01	-0.40*	0.25	-0.17	-0.14
		(-0.47)	(-0.03)	(-1.85)	(1.25)	(-0.97)	(-1.31)
	(3) 3.MotiveG × SimQ	0.14	0.14	-0.23	0.27	-0.14	-0.00
		(0.84)	(0.78)	(-1.58)	(1.31)	(-0.76)	(-0.03)
	(4) 4.MotiveG × SimQ	-0.24	-0.16	-0.86**	0.56**	-0.44**	-0.08
		(-1.17)	(-0.93)	(-2.37)	(2.20)	(-2.22)	(-0.77)
	(5) 5.MotiveG × SimQ	-0.08	0.20	-0.18	0.02	-0.41	-0.50**
		(-0.42)	(0.75)	(-0.98)	(0.08)	(-1.32)	(-2.71)
	N of Obs.	450	450	450	450	450	450
	Year FE	Yes	Yes	Yes	Yes	Yes	Yes
	AcqInd FE	Yes	Yes	Yes	Yes	Yes	Yes
	N of singletons excluded	2	2	2	2	2	2

Table 8, continued

Panel C: Statistically significant coefficients for similarity proxies within specific value-creation motive subgroups, derived from Wald tests of linear combinations of the coefficient estimates from Panel B, with *p*-values reported beneath coefficients

	(CGAIN)	(AGAIN)	(ACAR)	(RELTGAIN)	(TCAR)	(TGAIN)
	(1)	(2)	(3)	(4)	(5)	(6)
(a) Model (5): Similarity = SimPROD						
Cost efficiency (1)	**0.40****	**0.48****	**0.34***			
	0.027	**0.039**	**0.060**			
Enhance market position (1) + (2)				**-0.29***		
				0.080		
Geographic expansion (1) + (4)					**-0.31****	
					0.010	
Innovation resources (1) + (5)	**-0.90***					**-0.77****
	0.080					**0.041**
(c) Model (5): Similarity = SimQ						
Cost efficiency (1)			**0.39****			**0.14****
			0.019			**0.042**
Enrich product portfolio (1) + (3)	**0.30***	**0.21***				
	0.068	**0.062**				
Geographic expansion (1) + (4)					**-0.31***	
					0.060	
Innovation resources (1) + (5)			**0.21***	**-0.26****		**-0.36****
			0.071	**0.020**		**0.044**

Table 9: Long-Term Merger Performance

Table 9, Panel A, presents descriptive statistics for three alternative measures of long-run merger performance (ΔROA) across subgroups formed by splitting the sample at the median of each interfirm similarity measure. The panel also reports the results from univariate tests comparing the value distributions of these measures between low- and high-similarity subgroups. Differences in means are tested using Student's *t*-tests, and differences in medians are evaluated using Wilcoxon rank-sum tests. The final two columns report the mean difference and the two-sided *p*-values from median tests.

Panel B reports ordinary least squares (OLS) regression results from Model (6) examining the impact of each similarity proxy on long-run merger performance, separately for product similarity (***SimPROD***), geographic proximity (***GeoProx***), and Tobin's Q similarity (***SimQ***). Each row presents results from a distinct regression defined by the dependent variable (***DV***) and the similarity proxy employed.

$$DV = \alpha + \gamma Similarity + \beta_1 AcqSIZE + \beta_2 AcqRETURN + \beta_3 AcqLEV + \beta_4 AccqINSTOWN + \beta_5 AcqFAGE + \beta_6 TrgSIZE + \beta_7 TrgRETURN + \beta_8 TrgLEV + \beta_9 TrgINSTOWN + \beta_{10} TrgFAGE + AcqIndFE + YearFE + \varepsilon \quad (6)$$

The dependent variable (***DV***) is one of three measures of long-run merger performance, defined as follows:

- Δ***ROA[-1,+1]***: The change in return on assets (ROA) from the fiscal year prior to the merger announcement to the first fiscal year after merger completion. The pre-merger ROA is calculated as the weighted average of the merging firms' ROA, with weights based on the book value of total assets at the fiscal year-end prior to the merger announcement.
- Δ***ROA[-1,+2]***: The difference between the merged firm's ROA in the second fiscal year after merger completion and the weighted average ROA of the fiscal year prior to the merger announcement.
- Δ***ROA[-2,+2]***: The difference between the average ROA over the two fiscal years following the merger and the average weighted ROA over the two fiscal years preceding the merger announcement. Weights are based on the book value of total assets at the corresponding fiscal year-end for both firms.

SimPROD is a proxy for product similarity, measured as the cosine similarity of two firms' word usages in business descriptions, developed by Phillips and Hoberg (2010; 2016). ***GeoProx*** is a proxy for geographic proximity, calculated as the negative natural logarithm of one plus the geographic distance between firms. ***SimQ*** is a proxy for resource quality similarity, measured as the negative absolute difference in the natural logarithm of Tobin's Q. Firm-level controls are included for both acquirers and target firms. Prefixes ***Acq*** and ***Trg*** denote acquirer and target firm variables, respectively. ***SIZE*** is a proxy for firm size, measured as the natural logarithm of the book value of total assets. ***RETURN*** denotes the 12-month buy-and-hold cumulative abnormal return relative to the CRSP market index, measured over 12 months ending at two months prior to the merger announcement. ***LEV*** denotes the financial leverage ratio, calculated as the sum of current and long-term debt scaled by total assets. ***INSTOWN*** is the percentage of institutional ownership. ***FAGE*** represents firm age, calculated as the natural logarithm of the number of years since the firm's first appearance in the CRSP monthly data.

The estimation samples consist of the 452 operating synergy-driven mergers used in the shareholder wealth effect analyses, further restricted to those with non-missing values for the relevant long-run financial performance measures. All continuous variables are winsorized at the 1st and 99th percentiles based on the 452 mergers, and then standardized by subtracting the mean and dividing by the standard deviation of the estimation sample in each analysis. Standard errors are two-way clustered by acquirer industry and merger announcement year, and *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9, continued

Panel A: Summary statistics and univariate analyses of ΔROA between mergers with low versus high similarity

	N	Mean	SD	Median	N	Mean	SD	Median	T-test dif. in mean	Rank-sum test *p*-value
		Low SimPROD				High SimPROD				
ΔROA[-1,+1]	200	-0.012	0.047	-0.006	200	-0.004	0.033	-0.001	**-0.007***	0.169
ΔROA[-1,+2]	185	-0.008	0.049	-0.009	185	-0.002	0.035	-0.001	-0.006	**0.036**
ΔROA[-2,+2]	175	-0.008	0.047	-0.008	174	0.002	0.040	-0.001	**-0.010****	**0.030**
		Low GeoProx				High GeoProx				
ΔROA[-1,+1]	200	-0.010	0.046	-0.007	200	-0.006	0.034	0.000	-0.001	**0.047**
ΔROA[-1,+2]	185	-0.005	0.052	-0.008	185	-0.004	0.030	-0.001	0.000	**0.095**
ΔROA[-2,+2]	175	-0.002	0.053	-0.006	174	-0.004	0.033	-0.001	0.002	0.193
		Low SimQ				High SimQ				
ΔROA[-1,+1]	200	-0.014	0.050	-0.009	200	-0.002	0.027	0.000	**-0.013*****	**0.002**
ΔROA[-1,+2]	185	-0.010	0.052	-0.012	185	0.000	0.029	-0.001	**-0.010****	**0.003**
ΔROA[-2,+2]	175	-0.007	0.053	-0.010	174	0.000	0.032	-0.001	-0.007	**0.009**

Panel B: Coefficient estimates from Model (6) examining the effect of each similarity dimension on the long-run financial performance of operating synergy-driven mergers

	DV	Similarity	Coef.	*T*-stat.	N of Obs.	Adj. R^2	Controls	AcqInd FE	Year FE
(a)		SimPROD	0.18	(1.40)	398	0.09	Yes	Yes	Yes
(b)	ΔROA[-1,+1]	GeoProx	0.01	(0.09)	398	0.07	Yes	Yes	Yes
(c)		SimQ	0.14	(1.46)	398	0.08	Yes	Yes	Yes
(d)		SimPROD	0.16	(1.53)	368	0.09	Yes	Yes	Yes
(e)	ΔROA[-1,+2]	GeoProx	-0.03	(-0.36)	368	0.08	Yes	Yes	Yes
(f)		SimQ	0.06	(0.68)	368	0.08	Yes	Yes	Yes
(g)		SimPROD	0.17	(1.41)	347	0.17	Yes	Yes	Yes
(h)	ΔROA[-2,+2]	GeoProx	-0.02	(-0.33)	347	0.15	Yes	Yes	Yes
(i)		SimQ	0.07	(0.81)	347	0.16	Yes	Yes	Yes

Table 10: Synergy Mechanism: Interactive Effect of SimPROD and GeoProx

Table 10 presents coefficient estimates from Model (7), which analyzes the interactive effect of product similarity and geographic proximity on the likelihood of mergers motivated by operating synergies. Model (7) is a linear probit model with fixed effects at the matched actual-control merger group level, specified as follows. Control mergers are constructed by pairing each actual acquirer with up to five control target firms.

$$Deal = \alpha + \gamma_1 SimPROD + \gamma_2 GeoProx + \gamma_3 SimPROD \times GeoProx + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgRETURN + \beta_4 TrgLEV + \beta_5 TrgINSTOWN + \beta_6 TrgFAGE + GroupFE + \varepsilon \quad (7)$$

The dependent variable (***Deal***) equals one if the observation refers to an actual merger and zero otherwise. ***SimPROD*** is a proxy for product similarity, measured as the cosine similarity of two firms' word usages in business descriptions, developed by Phillips and Hoberg (2010; 2016). ***GeoProx*** is a proxy for geographic proximity, calculated as the negative natural logarithm of one plus the geographic distance between firms. ***RELSIZE*** is a proxy for the relative size of the target firm to the acquirer, measured as the market capitalization of the (control) target firm relative to that of the acquirer. Several control variables are included to account for target firm characteristics: ***TrgSIZE***, the natural logarithm of the book value of total assets; ***TrgRETURN***, the 12-month buy-and-hold cumulative abnormal return relative to the CRSP market index, measured over 12 months ending at two months prior to the merger announcement; ***TrgLEV***, the financial leverage ratio, calculated as the sum of current and long-term debt scaled by total assets; ***TrgINSTOWN***, the percentage of institutional ownership; and ***TrgFAGE***, firm age, calculated as the natural logarithm of the number of years since the firm's first appearance in the CRSP monthly data.

Columns report coefficient estimates from Model (7) across different estimation samples: column (1) presents results based on the pooled sample of operating synergy-driven mergers; columns (2) through (6) present results for subsamples categorized by distinct value-creation motives, including (2) improving cost efficiency, (3) enhancing market position, (4) enriching product portfolios, (5) geographic market expansion, and (6) acquiring innovation resources.

All continuous variables are winsorized at the 1st and 99th percentiles based on the pooled sample. Variables are then standardized by subtracting the mean and dividing by the standard deviation of the estimation sample in each analysis. Standard errors are clustered at the matched actual-control merger group level, and *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10, continued

	(Pooled sample)	(Cost efficiency)	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
	(1)	(2)	(3)	(4)	(5)	(6)
SimPROD	**0.26*** **	**0.30*** **	**0.19*** **	**0.26*** **	**0.17*** **	**0.28*** **
	(19.05)	**(5.50)**	**(8.39)**	**(14.64)**	**(5.95)**	**(7.01)**
GeoProx	**0.10*** **	**0.09** **	**0.16*** **	**0.05*** **	**0.18*** **	-0.03
	(10.76)	**(2.33)**	**(11.93)**	**(2.78)**	**(9.20)**	(-0.64)
SimPROD × GeoProx	**0.07*** **	**0.08*** **	**0.09*** **	0.00	0.03	-0.00
	(7.14)	**(3.02)**	**(6.85)**	(0.04)	(1.16)	(-0.03)
RelSIZE	-0.03**	-0.07	-0.03	-0.01	-0.03	-0.01
	(-2.20)	(-1.27)	(-1.60)	(-0.87)	(-0.74)	(-0.39)
TrgSIZE	0.06*	0.27**	0.06	0.02	0.05	0.03
	(1.73)	(2.53)	(1.27)	(0.33)	(0.72)	(0.34)
TrgRETURN	0.01	-0.01	-0.01	0.01	0.05**	0.02
	(0.94)	(-0.51)	(-0.80)	(0.78)	(2.16)	(0.58)
TrgLEV	0.02*	0.02	0.02	0.01	0.00	-0.04
	(1.66)	(0.44)	(1.46)	(0.54)	(0.23)	(-1.32)
TrgINSTOWN	0.07***	0.06*	0.06***	0.08***	0.06**	0.03
	(6.77)	(1.71)	(3.29)	(5.00)	(2.50)	(0.81)
TrgFAGE	-0.01	-0.03	-0.02	-0.02	0.04**	-0.00
	(-1.07)	(-1.28)	(-1.35)	(-1.60)	(2.35)	(-0.14)
Intercept	0.16***	0.16***	0.16***	0.18***	0.17***	0.18***
	(85.33)	(41.07)	(64.23)	(69.02)	(22.42)	(34.04)
N of Obs.	2,619	201	953	807	447	211
N of Groups	459	35	164	142	80	38
Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.31	0.40	0.37	0.32	0.33	0.29
Model test *p*-value	0.00	0.00	0.00	0.00	0.00	0.00

Table 11: Information Mechanism: Effect of the Opaqueness of Target Firms' Publicly Available Information

Table 11, columns (1), (3), (5), and (7) present coefficient estimates that examine whether ***SimPROD*** and ***GeoProx*** serve solely as proxies for reduced information asymmetry between firms that influence merger likelihood. To address this concern, a direct proxy for the opaqueness of target firms' publicly available information is added to Models (1) and (2) to assess the possibility. Two alternative proxies are employed: earnings quality (***DACC***) and the amount of firm-specific information incorporated into stock prices (***NonSynchronicity***). The adjusted conditional logit models are specified as follows, where ***Similarity*** represents either ***SimPROD*** or ***GeoProx***, and ***TrgInfo*** denotes either ***DACC*** or ***NonSynchronicity***, depending on the specification and as indicated by column titles.

$$Deal = \gamma_1 Similaity + \gamma_2 TrgInfo + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgRETURN + \beta_4 TrgLEV + \beta_5 TrgINSTOWN + \beta_6 TrgFAGE + GroupFE$$

Columns (2), (4), (6), and (8) provide coefficient estimates from the following linear probit model, Model (8), which examines whether these information opaqueness proxies moderate the positive effects of ***SimPROD*** and ***GeoProx*** on the likelihood of operating synergy-driven mergers.

$$Deal = \alpha + \gamma_1 Similaity + \gamma_2 TrgInfo + \gamma_3 Similarity \times TrgInfo + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgRETURN + \beta_4 TrgLEV + \beta_5 TrgINSTOWN + \beta_6 TrgFAGE + GroupFE + \varepsilon \quad (8)$$

In both models, the dependent variable (***Deal***) equals one if the observation refers to an actual merger and zero otherwise. ***SimPROD*** is a proxy for product similarity, measured as the cosine similarity of two firms' word usages in business descriptions, developed by Phillips and Hoberg (2010; 2016). ***GeoProx*** is a proxy for geographic proximity, calculated as the negative natural logarithm of one plus the geographic distance between firms. ***DACC*** is a proxy for the (control) target firm's earnings quality, measured as the absolute value of abnormal performance-adjusted discretionary accruals. ***NonSynchronicity*** is a proxy for the (control) target firm's stock return non-synchronicity, measured over the 12 months ending on June 30th prior to the merger announcement. ***RELSIZE*** is a proxy for the relative size of the target firm to the acquirer, measured as the market capitalization of the (control) target firm relative to that of the acquirer. Several control variables are included to account for target firm characteristics: ***TrgSIZE***, the natural logarithm of the book value of total assets; ***TrgRETURN***, the 12-month buy-and-hold cumulative abnormal return relative to the CRSP market index, measured over 12 months ending at two months prior to the merger announcement; ***TrgLEV***, the financial leverage ratio, calculated as the sum of current and long-term debt scaled by total assets; ***TrgINSTOWN***, the percentage of institutional ownership; and ***TrgFAGE***, firm age, calculated as the natural logarithm of the number of years since the firm's first appearance in the CRSP monthly data.

To illustrate, column (1) shows that ***SimPROD*** remains significantly positive after controlling for ***DACC***, which is statistically insignificant. This result suggests that ***SimPROD***'s effect on merger likelihood is not merely attributable to low information asymmetry. By contrast, column (6) shows that ***GeoProx*** is significantly positive; ***DACC*** is statistically insignificant; and the interaction term (***GeoProx*** × ***DACC***) is significantly negative. The results indicate that reduced information asymmetry contributes to explaining the effect of ***GeoProx*** on merger likelihood, with geographically proximate acquirers being less likely to select targets with higher levels of earnings management.

The estimation samples comprise the pooled sample of operating synergy-driven mergers, restricted to matched actual-control groups in which the actual target and at least one control target have non-missing values for the relevant measure of information opaqueness (***DACC*** or ***NonSynchronicity***), depending on the specification. All continuous variables are winsorized at the 1st and 99th percentiles based on the pooled sample. Variables are then standardized by subtracting the mean and dividing by the standard deviation of the estimation sample in each analysis. Standard errors are clustered at the matched actual-control merger group level, and *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11, continued

	(SimPROD)				(GeoProx)			
	(DACC)		(NonSynchronicity)		(DACC)		(NonSynchronicity)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Similarity	**2.34*****	**0.31*****	**2.30*****	**0.31*****	**0.78*****	**0.15*****	**0.72*****	**0.14*****
	(14.81)	**(24.15)**	**(14.08)**	**(23.05)**	**(11.38)**	**(14.50)**	**(10.86)**	**(12.94)**
TrgInfo	-0.01	0.01	0.09	0.01	0.01	0.00	0.01	0.00
	(-0.11)	(0.55)	(0.92)	(0.90)	(0.12)	(0.14)	(0.14)	(0.24)
Similarity × TrgInfo		0.01		0.00		**-0.05*****		**-0.03*****
		(1.30)		(0.11)		**(-4.43)**		**(-2.91)**
RelSIZE	-0.56***	-0.04***	-0.56***	-0.05***	-0.43***	-0.06***	-0.45***	-0.06***
	(-4.40)	(-3.73)	(-4.22)	(-3.76)	(-4.09)	(-4.62)	(-4.19)	(-4.79)
TrgSIZE	0.53*	0.05	0.64**	0.07*	0.78***	0.12***	0.92***	0.15***
	(1.80)	(1.46)	(2.06)	(1.93)	(3.44)	(3.50)	(3.86)	(3.97)
TrgRETURN	0.04	0.00	0.02	0.00	0.05	0.01	0.05	0.01
	(0.55)	(0.32)	(0.29)	(0.10)	(0.74)	(0.52)	(0.72)	(0.59)
TrgLEV	-0.03	0.02**	-0.02	0.02*	-0.05	-0.01	-0.07	-0.01
	(-0.37)	(2.02)	(-0.23)	(1.68)	(-0.67)	(-0.52)	(-0.90)	(-1.09)
TrgINSTOWN	0.61***	0.07***	0.57***	0.07***	0.67***	0.09***	0.57***	0.08***
	(5.46)	(5.92)	(5.32)	(5.83)	(6.88)	(7.72)	(6.55)	(7.42)
TrgFAGE	-0.01	-0.00	-0.05	-0.01	-0.14**	-0.02**	-0.16**	-0.03***
	(-0.12)	(-0.02)	(-0.69)	(-0.72)	(-2.22)	(-2.45)	(-2.52)	(-2.77)
Intercept		0.18***		0.18***		0.17***		0.18***
		(65.68)		(140.29)		(245.03)		(531.36)
N of Obs.	2,528	2,528	2,245	2,245	2,528	2,528	2,245	2,245
N of Groups	447	447	408	408	447	447	408	408
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.33		0.34		0.18		0.17	
Adj. R^2		0.22		0.23		0.16		0.14
Model test *p*-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 12: Information Mechanism: Effect of Alternative Private Information Channels

Table 12, columns (1), (3), (5), and (7) provide coefficient estimates examining whether ***SimPROD*** and ***GeoProx*** merely serve as proxies for low information asymmetry by controlling for the presence of an alternative pairwise private information channel. The analysis employs two proxies for such channels between firms: closely connected boards (***D1stConn***) and a common auditor (***CAudit***). The adjusted conditional logit model is specified as follows, where ***Similarity*** denotes either ***SimPROD*** or ***GeoProx***, and ***TrgInfo*** denotes either ***D1stConn*** or ***CAudit***, depending on the specification and as indicated by column titles.

$$Deal = \gamma_1 Similaity + \gamma_2 TrgInfo + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgRETURN + \beta_4 TrgLEV + \beta_5 TrgINSTOWN + \beta_6 TrgFAGE + GroupFE$$

Columns (2), (4), (6), and (8) present coefficient estimates from the following linear probit model, Model (8), which analyzes whether the presence of an alternative private information channel moderates the positive effects of *SimPROD* and *GeoProx* on the likelihood of operating synergy-driven mergers.

$$Deal = \alpha + \gamma_1 Similaity + \gamma_2 TrgInfo + \gamma_3 Similarity \times TrgInfo + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgRETURN + \beta_4 TrgLEV + \beta_5 TrgINSTOWN + \beta_6 TrgFAGE + GroupFE + \varepsilon \quad (8)$$

In both models, the dependent variable (***Deal***) equals one if the observation refers to an actual merger and zero otherwise. ***SimPROD*** is a proxy for product similarity, measured as the cosine similarity of two firms' word usages in business descriptions, developed by Phillips and Hoberg (2010; 2016). ***GeoProx*** is a proxy for geographic proximity, calculated as the negative natural logarithm of one plus the geographic distance between firms. ***D1stConn*** is an indicator variable equal to one if at least two directors from the respective boards of both (pseudo) merging firms obtained the same bachelor's degree or higher from the same institution within one year, or worked at the same third company for more than 365 days as of the beginning of the fiscal year before the merger announcement; zero otherwise. ***CAudit*** is an indicator variable equal to one if the same auditor issued audit opinions for both (pseudo) merging firms in the fiscal year preceding the merger announcement; zero otherwise. ***RELSIZE*** is a proxy for the relative size of the target firm to the acquirer, measured as the market capitalization of the (control) target firm relative to that of the acquirer. Several control variables are included to account for target firm characteristics: ***TrgSIZE***, the natural logarithm of the book value of total assets; ***TrgRETURN***, the 12-month buy-and-hold cumulative abnormal return relative to the CRSP market index, measured over 12 months ending at two months prior to the merger announcement; ***TrgLEV***, the financial leverage ratio, calculated as the sum of current and long-term debt scaled by total assets; ***TrgINSTOWN***, the percentage of institutional ownership; and ***TrgFAGE***, firm age, calculated as the natural logarithm of the number of years since the firm's first appearance in the CRSP monthly data.

For illustration, column (1) shows that ***SimPROD*** remains significantly positive after controlling for the presence of closely connected boards (***D1stConn***). This finding suggests that the positive relationship between ***SimPROD*** and merger likelihood cannot be attributed solely to ***SimPROD*** serving as a proxy for low information asymmetry. Column (6) reveals that while both ***GeoProx*** and ***D1stConn*** are significantly positive, their interaction term is significantly negative. The results indicate that the information asymmetry mechanism plays a role in explaining the relationship between ***GeoProx*** and merger likelihood. In particular, geographic proximity and closely connected boards may serve as substitute channels through which acquirers obtain information about potential target firms.

The estimation sample consists of the pooled sample of operating synergy-driven mergers. All continuous variables are winsorized at the 1st and 99th percentiles based on the pooled sample. Variables are then standardized by subtracting the sample mean and dividing by the sample standard deviation. Standard errors are clustered at the matched actual-control merger group level, and *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12, continued

	(SimPROD)				(GeoProx)			
	(D1stConn)		(CAudit)		(D1stConn)		(CAudit)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Similarity	**2.33*****	**0.30*****	**2.33*****	**0.29*****	**0.77*****	**0.16*****	**0.78*****	**0.15*****
	(15.16)	**(23.15)**	**(15.24)**	**(20.98)**	**(11.35)**	**(14.71)**	**(11.63)**	**(13.23)**
TrgInfo	**0.59****	**0.11*****	0.16	0.03	**0.46****	**0.13*****	0.18	0.03
	(2.50)	**(2.85)**	(1.02)	(1.34)	**(2.19)**	**(3.32)**	(1.26)	(1.32)
Similarity × TrgInfo		**0.09****		**0.07*****		**-0.09*****		-0.02
		(2.16)		**(3.25)**		**(-3.12)**		(-0.98)
RelSIZE	-0.48***	-0.04***	-0.50***	-0.04***	-0.40***	-0.05***	-0.41***	-0.05***
	(-3.82)	(-3.06)	(-3.98)	(-3.28)	(-3.86)	(-4.40)	(-4.04)	(-4.40)
TrgSIZE	0.44	0.04	0.51*	0.05	0.80***	0.13***	0.83***	0.13***
	(1.48)	(1.24)	(1.74)	(1.50)	(3.48)	(3.59)	(3.63)	(3.70)
TrgRETURN	0.06	0.00	0.05	0.00	0.06	0.01	0.06	0.01
	(0.80)	(0.48)	(0.67)	(0.31)	(0.88)	(0.70)	(0.86)	(0.70)
TrgLEV	-0.03	0.02**	-0.02	0.02*	-0.06	-0.01	-0.06	-0.01
	(-0.33)	(1.97)	(-0.21)	(1.91)	(-0.82)	(-1.03)	(-0.75)	(-0.81)
TrgInstOwn	0.58***	0.07***	0.60***	0.07***	0.63***	0.09***	0.64***	0.09***
	(5.38)	(5.95)	(5.48)	(5.88)	(6.70)	(7.57)	(6.86)	(7.55)
TrgFAGE	-0.01	-0.00	-0.01	-0.00	-0.14**	-0.02***	-0.14**	-0.02**
	(-0.20)	(-0.07)	(-0.18)	(-0.07)	(-2.28)	(-2.62)	(-2.28)	(-2.51)
Intercept		0.17***		0.17***		0.17***		0.17***
		(54.24)		(42.85)		(53.35)		(39.06)
N of Obs.	2,619	2,619	2,619	2,619	2,619	2,619	2,619	2,619
N of Groups	459	459	459	459	459	459	459	459
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.34		0.33		0.19		0.18	
Adj. R^2		0.23		0.22		0.15		0.14
Model test *p*-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 13: Validation Test of the Low Search Friction Assumption

Table 13, columns (1), (3), (5), and (7) present coefficient estimates examining whether controlling for the accessibility to target firms' information influences the effect of resource quality similarity (***SimQ***) on the likelihood of operating synergy-driven mergers. This analysis employs four proxies for information accessibility: two proxies for the opaqueness of target firms' publicly available information—earnings quality (***DACC***) or the amount of firm-specific information incorporated into stock prices (***NonSynchronicity***)—and two proxies for alternative pairwise private information channels—closely connected boards (***D1stConn***) and a common auditor (***CAudit***). The adjusted Model (3) is specified as follows, where ***TrgInfo*** denotes ***DACC***, ***NonSynchronicity***, ***D1stConn***, or ***CAudit*** in separate regression estimates, as indicated by column titles.

$$Deal = \gamma_1 SimQ + \gamma_2 TrgInfo + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgQ + \beta_4 TrgRETURN + \beta_5 TrgLEV + \beta_6 TrgINSTOWN + \beta_7 TrgROA + \beta_8 TrgFAGE + GroupFE$$

Columns (2), (4), (6), and (8) present coefficient estimates from the following linear probit model, which assesses whether the accessibility to target firms' information moderates the positive relationship between ***SimQ*** and the likelihood of operating synergy-driven mergers.

$$Deal = \alpha + \gamma_1 SimQ + \gamma_2 TrgInfo + \gamma_3 SimQ \times TrgInfo + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgQ + \beta_4 TrgRETURN + \beta_5 TrgLEV + \beta_6 TrgINSTOWN + \beta_7 TrgROA + \beta_8 TrgFAGE + GroupFE + \varepsilon$$

In both models, the dependent variable (***Deal***) equals one if the observation corresponds to an actual merger and zero otherwise. ***SimQ*** is a proxy for resource quality similarity, measured as the negative absolute difference in the natural logarithm of Tobin's Q. ***DACC*** is a proxy for the (control) target firm's earnings quality, measured as the absolute value of abnormal performance-adjusted discretionary accruals. ***NonSynchronicity*** is a proxy for the (control) target firm's stock return non-synchronicity, measured over the 12 months ending on June 30th prior to the merger announcement. ***D1stConn*** is an indicator variable equal to one if at least two directors from the respective boards of both (pseudo) merging firms obtained the same bachelor's degree or higher from the same institution within one year, or worked at the same third company for more than 365 days as of the beginning of the fiscal year before the merger announcement; zero otherwise. ***CAudit*** is an indicator variable equal to one if the same auditor issued audit opinions for both (pseudo) merging firms in the fiscal year preceding the merger announcement; zero otherwise. ***RELSIZE*** is a proxy for the relative size of the target firm to the acquirer, measured as the market capitalization of the (control) target firm relative to that of the acquirer. Several control variables are included to account for target firm characteristics: ***TrgSIZE***, the natural logarithm of the book value of total assets; ***TrgQ***, the market-to-book value of assets; ***TrgRETURN***, the 12-month buy-and-hold cumulative abnormal return relative to the CRSP market index, measured over 12 months ending at two months prior to the merger announcement; ***TrgLEV***, the financial leverage ratio, calculated as the sum of current and long-term debt scaled by total assets; ***TrgINSTOWN***, the percentage of institutional ownership; ***TrgROA***, return on assets, measured as operating income before depreciation scaled by total assets; and ***TrgFAGE***, firm age, calculated as the natural logarithm of the number of years since the firm's first appearance in the CRSP monthly data.

To illustrate, columns (2), (4), (6), and (8) show that ***SimQ*** remains significantly positive, and the interaction term of ***SimQ*** and ***TrgInfo*** remains statistically insignificant. The results suggest that the accessibility to target firms' information does not moderate the positive relationship between ***SimQ*** and merger likelihood, consistent with the assumption of low search friction faced by acquirers in operating synergy-driven mergers.

The estimation samples comprise the pooled sample of operating synergy-driven mergers, restricted to matched actual-control groups in which the actual target and at least one control target have non-missing values for the relevant measure of information accessibility (***DACC***, ***NonSynchronicity***, ***D1stConn***, or ***CAudit***), depending on the model specification. All continuous variables are winsorized at the 1st and 99th percentiles based on the pooled sample. Variables are then standardized by subtracting the mean and dividing by the standard deviation of the estimation sample in each analysis. Standard errors are clustered at the matched actual-control merger group level, and *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 13, continued

	(DACC)		(NonSynchronicity)		(D1stConn)		(CAudit)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SimQ	**0.22*** **	**0.03** **	**0.23*** **	**0.04*** **	**0.22*** **	**0.03*** **	**0.22*** **	**0.03*** **
	(2.93)	**(2.21)**	**(3.01)**	**(2.87)**	**(3.01)**	**(2.82)**	**(3.06)**	**(2.65)**
TrgInfo	-0.01	0.01	0.02	0.00	**0.78*** **	**0.16*** **	**0.27** **	**0.05** *
	(-0.09)	(0.51)	(0.22)	(0.33)	**(4.22)**	**(3.62)**	**(1.97)**	**(1.84)**
SimQ × TrgInfo		0.01		-0.00		-0.02		-0.00
		(1.45)		(-0.26)		(-0.58)		(-0.12)
RelSIZE	-0.62***	-0.10***	-0.62***	-0.10***	-0.58***	-0.09***	-0.60***	-0.09***
	(-5.75)	(-6.66)	(-5.70)	(-6.30)	(-5.40)	(-6.08)	(-5.79)	(-6.42)
TrgSIZE	1.10***	0.19***	1.23***	0.22***	1.06***	0.18***	1.12***	0.19***
	(4.71)	(4.84)	(4.80)	(4.92)	(4.51)	(4.59)	(4.79)	(4.82)
TrgQ	0.00	-0.00	-0.00	-0.00	0.37***	0.06***	0.01	0.00
	(0.06)	(-0.13)	(-0.06)	(-0.14)	(4.25)	(4.11)	(0.24)	(0.10)
TrgRETURN	-0.09	-0.02	-0.11	-0.02*	0.02	0.00	-0.09	-0.02
	(-1.41)	(-1.57)	(-1.61)	(-1.71)	(0.29)	(0.13)	(-1.40)	(-1.50)
TrgLEV	0.56***	0.09***	0.51***	0.08***	-0.10	-0.02	0.54***	0.08***
	(6.37)	(7.04)	(6.18)	(6.92)	(-1.48)	(-1.62)	(6.34)	(6.96)
TrgInstOwn	-0.09	-0.02*	-0.13**	-0.02**	0.53***	0.08***	-0.09	-0.02*
	(-1.56)	(-1.67)	(-2.15)	(-2.30)	(6.21)	(6.86)	(-1.56)	(-1.75)
TrgROA	0.37***	0.07***	0.35***	0.06***	-0.09	-0.02	0.38***	0.06***
	(4.27)	(4.40)	(3.95)	(3.86)	(-1.43)	(-1.46)	(4.44)	(4.32)
TrgFAGE	-0.10	-0.02*	-0.08	-0.01	-0.09	-0.02*	-0.09	-0.02
	(-1.60)	(-1.73)	(-1.19)	(-1.27)	(-1.61)	(-1.77)	(-1.48)	(-1.50)
Intercept		0.18***		0.18***		0.16***		0.17***
		(83.17)		(157.49)		(49.16)		(35.91)
N of Obs.	2,528	2,528	2,245	2,245	2,619	2,619	2,619	2,619
N of Groups	447	447	408	408	459	459	459	459
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.05		0.05		0.06		0.05	
Adj. R^2		0.03		0.03		0.04		0.03
Model test *p*-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 14: Moderating Effect of the Substitutability of Target Resources

Table 14, **Panel A**, presents descriptive statistics for three alternative measures reflecting target firms' industry-level resource substitutability. The measures are calculated following Ahern (2012), based on the BEA Input-Output (IO) summary-level industry classification. For each year, the three measures are calculated for all IO industries, excluding government sectors. Higher values of each proxy indicate lower resource substitutability and greater heterogeneity in resource quality among firms within an industry.

- ***ioindPM***: A proxy for industry profit margin, calculated as value added divided by total industry output for each IO industry year, based on the BEA USE table.
- ***ioindPMSD***: A proxy for dispersion in industry profit margins, measured as the standard deviation of firm-level profit margins within each IO industry year.
- ***ioindHHI***: Industry concentration ratio, measured as the Herfindahl-Hirschman Index (HHI) of firm-level sales revenues (Compustat item ***SALE***) within each IO industry year.

Panel A presents the frequency distribution of the 459 sample mergers across the six categories, benchmarking the sample targets' industry-level resource substitutability against the broader industrial economy.

Panel B presents coefficient estimates from the following linear probit model, which tests whether the resource quality heterogeneity of the target firm's industry moderates the effect of ***SimQ*** on the likelihood of operating synergy-driven mergers.

$$Deal = \alpha + \gamma_1 SimQ + \gamma_2 SimQ \times CAT + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgQ + \beta_4 TrgRETURN + \beta_5 TrgLEV + \beta_6 TrgINSTOWN + \beta_7 TrgROA + \beta_8 TrgFAGE + GroupFE + \varepsilon$$

The dependent variable (***Deal***) equals one if the observation refers to an actual merger and zero otherwise. ***SimQ*** is a proxy for resource quality similarity, measured as the negative absolute difference in the natural logarithm of Tobin's Q. ***CAT*** denotes ***HIGH*** or ***MOD***, two indicators for classifying the resource quality heterogeneity of sample industries. ***HIGH*** equals one if resource quality heterogeneity of the target industry is above the sample median (high level), and zero otherwise (low level); ***MOD*** equals one if it falls within the middle three quintiles of the sample distribution (moderate level), and zero otherwise (tails). ***RELSIZE*** is a proxy for the relative size of the target firm to the acquirer, measured as the market capitalization of the (control) target firm relative to that of the acquirer. Several control variables are included to account for target firm characteristics: ***TrgSIZE***, the natural logarithm of the book value of total assets; ***TrgQ***, the market-to-book value of total assets; ***TrgRETURN***, the 12-month buy-and-hold cumulative abnormal return relative to the CRSP market index, measured over 12 months ending at two months prior to the merger announcement; ***TrgLEV***, the financial leverage ratio, calculated as the sum of current and long-term debt scaled by total assets; ***TrgINSTOWN***, the percentage of institutional ownership; ***TrgROA***, return on assets, measured as operating income before depreciation scaled by total assets; and ***TrgFAGE***, firm age, calculated as the natural logarithm of the number of years since the firm's first appearance in the CRSP monthly data.

Columns in **Panel B** report coefficient estimates from the linear probit model using alternative definitions of ***CAT***, which is constructed based on alternative proxies for industry-level resource quality heterogeneity—***ioindPM***, ***ioindPMSD***, and ***ioindHHI***—and corresponding categorical indicators for heterogeneity level classification (***HIGH*** or ***MOD***), as specified in the column headers. One-tailed *t*-tests of the coefficient on ***SimQ*** within each heterogeneity-level subgroup are reported in *italics* in the rows highlighted in light grey. Coefficients on ***SimQ*** that are statistically significant based on one-tailed tests are shown in **bold**, with the associated *p*-values reported beneath the coefficients.

The estimation sample consists of the pooled sample of operating synergy-driven mergers. All continuous variables are winsorized at the 1st and 99th percentiles based on the pooled sample. Variables are then standardized by subtracting the mean and dividing by the standard deviation of the estimation sample. Standard errors are clustered at the matched actual-control merger group level, and *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 14, continued

Panel A: Frequency distribution of the sample mergers by target industry-level resource quality heterogeneity

Classification criteria: Median split across all IO industries each year	N	Below median	Above median
IO industry-level profit margin (*ioindPM*)	459	142	317
The standard deviation of within-industry profit margins (*ioindPMSD*)	459	57	402
Industry concentration ratio based on Compustat sales (*ioindHHI*)	459	408	51

Panel B: Coefficient estimates of the linear probit models analyzing whether resource quality heterogeneity among potential targets moderates the relationship between *SimQ* and merger likelihood

	ioindPM		ioindPMSD		ioindHHI	
	HIGH	MOD	HIGH	MOD	HIGH	MOD
	(1)	(2)	(3)	(4)	(5)	(6)
SimQ	0.02	0.01	0.02	0.04***	0.03	0.06***
	(1.59)	(0.62)	(1.08)	(2.61)	(1.40)	(3.10)
SimQ	*0.02*	*0.01*	*0.02*	***0.04******	*0.03*	***0.06*****
p-value of one-tailed test	*0.056*	*0.268*	*0.281*	***0.005***	*0.081*	***0.001***
CAT × SimQ	0.03	0.04	0.02	-0.02	0.00	-0.04*
	(1.02)	(1.59)	(0.62)	(-0.95)	(0.04)	(-1.78)
SimQ+ CAT× SimQ	***0.05****	***0.05*****	***0.04*****	*0.02*	***0.03****	*0.02*
p-value of one-tailed test	***0.012***	***0.002***	***0.006***	*0.110*	***0.010***	*0.118*
CAT	(No estimates; absorbed by group fixed effects)					
RelSIZE	-0.09***	-0.09***	-0.09***	-0.09***	-0.09***	-0.09***
	(-6.37)	(-6.26)	(-6.39)	(-6.39)	(-6.39)	(-6.39)
TrgSIZE	0.19***	0.20***	0.19***	0.20***	0.20***	0.19***
	(4.82)	(4.95)	(4.93)	(4.92)	(4.89)	(4.91)
TrgQ	0.06***	0.06***	0.06***	0.06***	0.06***	0.06***
	(4.18)	(4.25)	(4.32)	(4.30)	(4.27)	(4.20)
TrgRETURN	0.00	0.00	0.00	0.00	0.00	0.00
	(0.11)	(0.10)	(0.08)	(0.06)	(0.06)	(0.02)
TrgLEV	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(-1.56)	(-1.54)	(-1.55)	(-1.55)	(-1.55)	(-1.54)
TrgINSTOWN	0.08***	0.08***	0.08***	0.08***	0.08***	0.08***
	(7.04)	(7.00)	(6.99)	(7.02)	(7.02)	(7.06)
TrgROA	-0.02	-0.02*	-0.02	-0.02	-0.02	-0.02
	(-1.58)	(-1.73)	(-1.62)	(-1.64)	(-1.60)	(-1.53)
TrgFAGE	-0.02*	-0.02*	-0.02*	-0.02*	-0.02*	-0.02*
	(-1.84)	(-1.88)	(-1.77)	(-1.80)	(-1.82)	(-1.88)
Intercept	0.17***	0.17***	0.18***	0.18***	0.18***	0.17***
	(49.35)	(180.79)	(63.10)	(76.27)	(56.65)	(140.83)
N of Obs.	2,619	2,619	2,619	2,619	2,619	2,619
N of Groups	459	459	459	459	459	459
Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.03	0.03	0.03	0.03	0.03	0.03
Model test *p*-value	0.00	0.00	0.00	0.00	0.00	0.00

Table 15: Effect of Acquirer Entrenchment

Table 15 examines how acquirers' entrenchment levels influence the effects of product similarity (***SimPROD***), geographic proximity (***GeoProx***), and Tobin's Q similarity (***SimQ***) on target selection and shareholder wealth outcomes. Acquirer entrenchment is measured using the E-Index developed by Bebchuk et al. (2009).

Requiring non-missing values of the acquirer E-Index reduces the sample size to

- 339 matched actual-control merger groups (1,936 observations) for target selection analyses and
- 334 mergers for shareholder wealth effect analyses.

An indicator variable, ***Eindex_HIGH***, is constructed to classify acquirers into high- and low-entrenchment groups: ***Eindex_HIGH*** equals one if the acquirer's E-Index exceeds the sample median, and zero otherwise. Notably, E-Index data is available only for firms included in the S&P 1500 index. Data prior to 2007 were obtained from Professor Bebchuk's website, while data from 2007 onward were compiled using the ISS ESG Governance database.

Panel A replicates coefficient estimates for ***SimPROD***, ***GeoProx***, and ***SimQ*** from Models (1), (2), and (3), respectively, analyzing their effects on merger likelihood using the reduced sample with available E-Index data.

Panel B presents coefficient estimates from the following linear probit models, which examine whether acquirers' entrenchment level (***Eindex_HIGH***) influences their preferences for product similarity, geographic proximity, and resource quality similarity, respectively, when selecting target firms. *Similarity* denotes ***SimPROD***, ***GeoProx***, and ***SimQ***, and the lists of control variables are the same as Models (1)–(3), respectively. The models include fixed effects at the matched actual-control merger group level. Standard errors are clustered at the same level, and *t*-statistics are reported in parentheses. Additionally, I test the statistical significance of (***Similarity*** + ***Similarity*** × ***Eindex_HIGH***), which represents the effect of the similarity proxy on merger likelihood within the high-entrenchment subgroup. The results are reported in *italics* in the rows highlighted in light grey, with *p*-values reported beneath the corresponding combined coefficients.

$$Deal = \alpha + (\gamma Similarity + Controls) \times Eindex\_HIGH + GroupFE + \varepsilon$$

Column titles denote distinct estimation samples: (1) the pooled sample of operating synergy-driven mergers, (2) the subsample aimed at improving cost efficiency, (3) the subsample aimed at enhancing market position, (4) the subsample motivated by enriching product portfolio, (5) the subsample aimed at expanding into new geographic markets, and (6) the subsample aimed at acquiring innovation resources.

Panel C replicates coefficient estimates for ***SimPROD***, ***GeoProx***, and ***SimQ*** from separate OLS regressions of Model (4), assessing their impact on shareholder wealth outcomes using the reduced sample with available E-Index data.

Panel D presents coefficient estimates for each similarity proxy and its interaction with ***Eindex_HIGH*** in an augmented Model (4), specified as follows.

$$DV = \alpha + \gamma_1 Similarity + \gamma_2 Eindex\_HIGH + \gamma_3 Similarity \times Eindex\_HIGH + Controls + AcqIndFE + YearFE + \varepsilon$$

Column titles denote specific shareholder wealth outcome measures. Models include fixed effects for the acquirer industry and merger announcement year. Standard errors are two-way clustered by the same dimensions, and *t*-statistics are reported in parentheses. Additionally, I test the statistical significance of (***Similarity*** + ***Similarity*** × ***Eindex_HIGH***), which represents the effect of the similarity proxy on specific shareholder wealth outcome measures within the high-entrenchment subgroup. The results are reported in rows highlighted in light grey, with *p*-values reported beneath the corresponding combined coefficients.

All continuous variables are winsorized at the 1st and 99th percentiles based on the relevant pooled sample. These variables are then standardized by subtracting the mean and dividing by the standard deviation of the estimation sample in each analysis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 15, continued

Panel A: Coefficient estimates for *SimPROD*, *GeoProx*, and *SimQ* from Models (1), (2), and (3), respectively

		(Pooled sample)	(Cost efficiency)	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
		(1)	(2)	(3)	(4)	(5)	(6)
(a)	SimPROD	**2.13*** **	**2.73*** **	**1.85*** **	**1.73*** **	**1.76*** **	**2.51*** **
		(12.42)	**(2.71)**	**(6.95)**	**(7.53)**	**(3.63)**	**(3.80)**
(b)	GeoProx	**0.73*** **	0.38	**1.17*** **	**0.48*** **	**1.48*** **	-0.04
		(10.02)	(1.04)	**(7.32)**	**(4.31)**	**(4.13)**	(-0.20)
(c)	SimQ	**0.23*** **	0.30	**0.30** **	**0.27** **	-0.03	**0.62***
		(2.82)	(0.61)	**(2.07)**	**(2.18)**	(-0.13)	**(1.89)**
N of Obs.		1,936	119	685	687	264	181
N of Groups		339	21	118	121	47	32

Panel B: Effect of acquirer entrenchment level on the relationships between similarity proxies and merger likelihood

		(Pooled sample)	(Cost efficiency)	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
		(1)	(2)	(3)	(4)	(5)	(6)
(a)	SimPROD	**0.27*** **	**0.24*** **	**0.23*** **	**0.23*** **	**0.23*** **	**0.20*** **
		(14.64)	**(6.10)**	**(7.49)**	**(9.85)**	**(3.39)**	**(5.56)**
	SimPROD × Eindex_HIGH	**0.07** **	-0.02	0.03	**0.08** **	0.02	**0.21*** **
		(2.13)	(-0.28)	(0.59)	**(2.28)**	(0.14)	**(3.87)**
	Eindex_HIGH=1: SimPROD	***0.34***	***0.22***	***0.26***	***0.31***	***0.25***	***0.41***
	Sum: two-sided p-value	***0.000***	***0.004***	***0.000***	***0.000***	***0.007***	***0.000***
(b)	GeoProx	**0.11*** **	0.04	**0.18*** **	**0.09*** **	**0.18*** **	-0.03
		(7.91)	(0.52)	**(8.98)**	**(3.65)**	**(4.84)**	(-0.71)
	GeoProx × Eindex_HIGH	**0.09*** **	**0.22** **	**0.06***	0.00	**0.09***	0.14
		(3.45)	**(2.39)**	**(1.90)**	(0.04)	**(1.99)**	(1.43)
	Eindex_HIGH=1: GeoProx	***0.20***	***0.26***	***0.24***	***0.09***	***0.27***	*0.11*
	Sum: two-sided p-value	***0.000***	***0.000***	***0.000***	***0.007***	***0.000***	*0.222*
(c)	SimQ	0.01	0.11	0.02	0.01	0.00	0.04
		(0.95)	(1.26)	(1.16)	(0.51)	(0.04)	(1.01)
	SimQ × Eindex_HIGH	**0.08** **	-0.11	**0.13** **	**0.08** **	-0.04	0.02
		(2.59)	(-0.81)	**(2.52)**	**(2.18)**	(-0.38)	(0.15)
	Eindex_HIGH=1: SimQ	***0.09***	*0.00*	***0.15***	***0.09***	*-0.04*	*0.06*
	Sum: two-sided p-value	***0.000***	*0.981*	***0.002***	***0.001***	*0.699*	*0.650*

Table 15, continued

Panel C: Coefficient estimates from Model (4), analyzing the effects of product similarity (*SimPROD*), geographic proximity (*GeoProx*), and resource quality similarity (*SimQ*) on shareholder wealth outcomes, separately

		(CGAIN)	(AGAIN)	(ACAR)	(RELTGAIN)	(TCAR)	(TGAIN)
		(1)	(2)	(3)	(4)	(5)	(6)
(a)	SimPROD	0.20	0.11	**0.15***	**-0.15****	-0.03	0.08
		(1.37)	(1.67)	**(1.93)**	**(-2.23)**	(-0.38)	(0.74)
(b)	GeoProx	-0.00	-0.06	0.04	-0.01	-0.03	**0.07***
		(-0.05)	(-0.73)	(0.55)	(-0.10)	(-0.40)	**(2.16)**
(c)	SimQ	0.07	0.09	0.02	0.00	-0.05	-0.03
		(1.39)	(1.46)	(0.33)	(0.03)	(-1.17)	(-0.67)

Panel D: Effect of acquirer entrenchment level on the effects of similarity proxies on shareholder wealth outcomes

		(CGAIN)	(AGAIN)	(ACAR)	(RELTGAIN)	(TCAR)	(TGAIN)
		(1)	(2)	(3)	(4)	(5)	(6)
(a)	SimPROD	0.19	0.11	**0.20****	**-0.20*****	-0.06	0.06
		(1.29)	(1.39)	**(2.78)**	**(-3.33)**	(-0.55)	(0.57)
	SimPROD × EIndex_HIGH	0.01	-0.02	-0.15	**0.17***	0.07	0.06
		(0.20)	(-0.18)	(-1.68)	**(1.91)**	(0.72)	(0.73)
	Eindex_HIGH=1: SimPROD	*0.20*	*0.09*	*0.05*	*-0.03*	*0.01*	*0.12*
	Sum: two-sided p-value	*0.172*	*0.143*	*0.714*	*0.806*	*0.926*	*0.383*
(b)	GeoProx	-0.02	-0.10	0.10	-0.00	-0.03	**0.11***
		(-0.17)	(-0.98)	(1.34)	(-0.02)	(-0.30)	**(2.08)**
	GeoProx × EIndex_HIGH	0.04	**0.13****	**-0.19***	-0.02	0.01	-0.11
		(0.47)	**(2.18)**	**(-2.09)**	(-0.28)	(0.04)	(-1.36)
	Eindex_HIGH=1: GeoProx	*0.02*	*0.03*	*-0.09*	*-0.02*	*-0.02*	*0.00*
	Sum: two-sided p-value	*0.632*	*0.589*	*0.392*	*0.773*	*0.749*	*0.960*
(c)	SimQ	0.05	**0.10***	0.01	-0.06	**-0.12*****	**-0.09***
		(0.69)	**(1.89)**	(0.24)	(-0.88)	**(-3.17)**	**(-1.90)**
	SimQ × EIndex_HIGH	0.12	-0.06	0.03	**0.22***	**0.29****	0.26
		(1.53)	(-0.68)	(0.25)	**(1.93)**	**(2.92)**	(1.77)
	Eindex_HIGH=1: SimQ	***0.17***	*0.04*	*0.04*	*0.16*	*0.17*	*0.17*
	Sum: two-sided p-value	***0.028***	*0.682*	*0.746*	*0.268*	*0.103*	*0.185*

Robustness Analyses

Table 16: Assess Potential Nonlinearity in the Relationship between SimPROD and Merger Likelihood

Table 16 presents coefficient estimates from the following linear probit model. This analysis examines potential nonlinearity in the relationship between ***SimPROD*** and the likelihood of operating synergy-driven mergers. The model is specified as follows, with variable definitions provided in Appendix A.

$$Deal = \alpha + \gamma_1 SimPROD + \gamma_2 SimPROD^2 + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgRETURN + \beta_4 TrgLEV + \beta_5 TrgINSTOWN + \beta_6 TrgFAGE + GroupFE + \varepsilon$$

Column titles indicate different estimation samples: column (1) presents results based on the pooled sample of operating synergy-driven mergers; columns (2) through (6) present results for subsamples categorized by distinct value-creation motives, including (2) improving cost efficiency, (3) enhancing market position, (4) enriching product portfolios, (5) geographic market expansion, and (6) acquiring innovation resources. All continuous variables are winsorized at the 1st and 99th percentiles based on the pooled sample. Variables are then standardized by subtracting the mean and dividing by the standard deviation of the estimation sample in each analysis. Standard errors are clustered at the matched actual-control merger group level, and *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(Pooled sample)	(Cost efficiency)	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
	(1)	(2)	(3)	(4)	(5)	(6)
SimPROD	**0.31*** **	**0.32*** **	**0.26*** **	**0.26*** **	**0.23*** **	**0.26*** **
	(25.05)	**(6.05)**	**(12.89)**	**(13.90)**	**(7.50)**	**(7.29)**
$SimPROD^2$	-0.01	0.01	0.01	0.01	0.00	**0.04****
	(-0.54)	(0.30)	(0.53)	(1.10)	(0.00)	**(2.27)**
RelSIZE	-0.04***	-0.10*	-0.05**	-0.01	-0.05	0.00
	(-3.38)	(-1.78)	(-2.47)	(-0.76)	(-1.40)	(0.07)
TrgSIZE	0.05	0.30***	0.05	-0.00	0.01	0.01
	(1.48)	(2.93)	(0.98)	(-0.07)	(0.15)	(0.07)
TrgRETURN	0.00	-0.02	-0.02	0.01	0.03	0.02
	(0.42)	(-0.93)	(-1.07)	(0.74)	(1.63)	(0.45)
TrgLEV	0.02**	0.03	0.03**	0.01	0.02	-0.04
	(1.99)	(0.64)	(2.00)	(0.41)	(1.30)	(-1.28)
TrgINSTOWN	0.07***	0.06	0.06***	0.08***	0.04	0.06
	(5.97)	(1.55)	(3.24)	(5.02)	(1.51)	(1.54)
TrgFAGE	-0.00	-0.03	-0.00	-0.02	0.06***	-0.01
	(-0.14)	(-1.08)	(-0.04)	(-1.48)	(3.27)	(-0.35)
Intercept	0.18***	0.16***	0.16***	0.16***	0.18***	0.14***
	(18.31)	(3.60)	(10.12)	(15.54)	(7.51)	(7.26)
N of Obs.	2,619	201	953	807	447	211
N of Groups	459	35	164	142	80	38
Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-2	0.22	0.30	0.17	0.31	0.14	0.30
Model test *p*-value	0.00	0.00	0.00	0.00	0.00	0.00

Table 17: Alternative Measure of Product Similarity

Table 17 replicates the analyses from Table 4 using an alternative measure of product similarity: an indicator variable equal to one if the (control) merging firms share the same 6-digit NAICS code (***SimNAICS***). **Panel A** presents coefficient estimates from the following conditional logit model. All other variables are defined as in Table 4. Column titles indicate different estimation samples.

$$Deal = \gamma SimNAICS + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgRETURN + \beta_4 TrgLEV + \beta_5 TrgINSTOWN + \beta_6 TrgFAGE + GroupFE$$

Panel B reports *p*-values from pairwise Wald tests assessing whether the coefficients on ***SimNAICS*** across subgroup analyses in Panel A, columns (2)–(6), differ significantly from one another (i.e., whether their confidence intervals do not overlap). All continuous variables are winsorized at the 1st and 99th percentiles based on the pooled sample. Variables are then standardized by subtracting the mean and dividing by the standard deviation of the estimation sample in each analysis. Standard errors are clustered at the matched actual-control merger group level, and *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Coefficient estimates from Model (1) using an alternative measure of product similarity—*SimNAICS*

	(Pooled sample)	(Cost efficiency)	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
	(1)	(2)	(3)	(4)	(5)	(6)
SimNAICS	**1.40*** **	**2.56*** **	**1.37*** **	**2.41*** **	0.19	0.46
	(8.89)	**(3.43)**	**(4.96)**	**(7.44)**	(0.48)	(1.04)
RelSIZE	-0.45***	-0.87**	-0.50***	-0.10	-0.58**	-0.58
	(-4.79)	(-2.15)	(-2.90)	(-0.86)	(-2.20)	(-1.61)
TrgSIZE	0.69***	2.11**	0.83**	0.18	0.68	-0.19
	(3.25)	(2.35)	(2.15)	(0.53)	(1.47)	(-0.30)
TrgRETURN	0.01	-0.47*	-0.13	0.07	0.18	0.20
	(0.16)	(-1.80)	(-1.15)	(0.62)	(1.30)	(0.92)
TrgLEV	0.00	0.37	0.01	0.01	-0.19	-0.28
	(0.02)	(1.34)	(0.11)	(0.04)	(-1.18)	(-1.16)
TrgInstOwn	0.63***	0.32	0.57***	0.84***	0.22	0.81**
	(6.66)	(0.81)	(3.54)	(4.86)	(1.14)	(2.12)
TrgFAGE	-0.10*	0.01	-0.08	-0.29**	0.33**	-0.39**
	(-1.69)	(0.05)	(-0.81)	(-2.34)	(2.16)	(-2.12)
N of Obs.	2,619	201	953	807	447	211
N of Groups	459	35	164	142	80	38
Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.10	0.32	0.09	0.23	0.05	0.11
Model test *p*-value	0.00	0.01	0.00	0.00	0.03	0.01
Link Test						
p-value of _hat	0.000	0.000	0.000	0.000	0.000	0.000
p-value of _hatsq	0.144	0.147	0.300	0.352	0.822	0.961

Panel B: Wald tests of pairwise differences in the coefficients on *SimNAICS* across subgroup analyses

Wald test *p*-values are reported.	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
	(3)	(4)	(5)	(6)
(2) Cost efficiency	0.132	0.854	**0.004**	**0.015**
(3) Market position		**0.015**	**0.012**	**0.078**
(4) Product portfolio			**0.000**	**0.000**
(5) Geo expansion				0.637

Table 18: Alternative Measure of Geographic Proximity

Table 18 replicates the analyses presented in Table 5, employing an alternative measure of geographic proximity: an indicator variable equal to one if the (control) merging firms are headquartered in the same Metropolitan Statistical Area (MSA) (***SimMSA***). **Panel A** reports coefficient estimates from the following conditional logit model, specified as follows. All other variables are defined as in Table 5. Column titles denote different estimation samples.

$$Deal = \gamma SimMSA + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgRETURN + \beta_4 TrgLEV + \beta_5 TrgINSTOWN + \beta_6 TrgFAGE + GroupFE$$

Panel B presents *p*-values from pairwise Wald tests assessing whether the coefficients on ***SimMSA*** across subgroup analyses in Panel A, columns (2)–(6), differ significantly from one another (i.e., whether their confidence intervals do not overlap). All continuous variables are winsorized at the 1st and 99th percentiles based on the pooled sample. Variables are then standardized by subtracting the mean and dividing by the standard deviation of the estimation sample in each analysis. Standard errors are clustered at the matched actual-control merger group level, and *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Coefficient estimates from Model (2) using an alternative measure of geographic proximity—*SimMSA*

	(Pooled sample)	(Cost efficiency)	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
	(1)	(2)	(3)	(4)	(5)	(6)
SimMSA	**2.06*** **	**2.66*** **	**2.86*** **	**1.47*** **	**2.40*** **	0.47
	(10.58)	**(3.12)**	**(8.54)**	**(4.17)**	**(4.03)**	(0.66)
RelSIZE	-0.40***	-0.94**	-0.37**	-0.13	-0.55**	-0.56
	(-4.14)	(-2.45)	(-2.06)	(-1.27)	(-2.09)	(-1.52)
TrgSIZE	0.76***	2.27**	0.92**	0.23	0.70	-0.29
	(3.41)	(2.18)	(2.12)	(0.66)	(1.52)	(-0.45)
TrgRETURN	0.02	-0.34	-0.14	0.09	0.18	0.18
	(0.22)	(-1.43)	(-0.96)	(0.70)	(1.12)	(0.82)
TrgLEV	-0.06	0.20	-0.14	0.01	-0.22	-0.28
	(-0.85)	(0.48)	(-1.11)	(0.06)	(-1.37)	(-1.10)
TrgInstOwn	0.60***	0.96**	0.45***	0.83***	0.25	0.83**
	(6.56)	(1.99)	(2.84)	(5.81)	(1.28)	(2.06)
TrgFAGE	-0.11*	-0.09	-0.10	-0.30***	0.38**	-0.43**
	(-1.90)	(-0.34)	(-0.95)	(-2.77)	(2.29)	(-2.46)
N of Obs.	2,619	201	953	807	447	211
N of Groups	459	35	164	142	80	38
Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.12	0.29	0.20	0.12	0.11	0.11
Model test *p*-value	0.00	0.01	0.00	0.00	0.00	0.00
Link Test						
p-value of _hat	0.000	0.000	0.000	0.000	0.000	0.001
p-value of _hatsq	0.175	0.900	0.933	0.391	0.780	0.608

Panel B: Wald tests of pairwise differences in the coefficients on *SimMSA* across subgroup analyses

Wald test *p*-values are reported.	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
	(3)	(4)	(5)	(6)
(2) Cost efficiency	0.822	0.193	0.804	**0.048**
(3) Market position		**0.004**	0.500	**0.002**
(4) Product portfolio			0.177	0.206
(5) Geo expansion				**0.037**

Table 19: Alternative Specification of Model (3)—Excluding TrgQ

Table 19 replicates the analyses presented in Table 6 using an alternative specification of the conditional logit model—Model (3)—by excluding ***TrgQ***. **Panel A** presents coefficient estimates for the conditional logit model specified as follows. All other variables are defined as in Table 6. Column titles indicate different estimation samples.

$$Deal = \gamma SimQ + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgRETURN + \beta_4 TrgLEV + \beta_5 TrgINSTOWN + \beta_6 TrgROA + \beta_7 TrgFAGE + GroupFE$$

Panel B presents *p*-values from pairwise Wald tests assessing whether the coefficients on ***SimQ*** across subgroup analyses in Panel A, columns (2)–(6), differ significantly from one another (i.e., whether their confidence intervals do not overlap). All continuous variables are winsorized at the 1st and 99th percentiles based on the pooled sample. Variables are then standardized by subtracting the mean and dividing by the standard deviation of the estimation sample in each analysis. Standard errors are clustered at the matched actual-control merger group level, and *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Coefficient estimates from an alternative specification of Model (3) by excluding *TrgQ*

	(Pooled sample)	(Cost efficiency)	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
	(1)	(2)	(3)	(4)	(5)	(6)
SimQ	**0.13***	0.30	0.18	**0.25****	0.02	0.07
	(1.68)	(0.89)	(1.48)	**(2.15)**	(0.17)	(0.32)
RelSIZE	-0.42***	-0.93**	-0.52***	-0.13	-0.63**	-0.61
	(-4.56)	(-2.25)	(-3.17)	(-1.25)	(-2.17)	(-1.61)
TrgSIZE	0.81***	3.02***	1.13***	-0.02	0.80*	0.66
	(3.50)	(2.76)	(2.84)	(-0.07)	(1.78)	(1.03)
TrgRETURN	0.01	-0.32	-0.15	0.07	0.17	0.13
	(0.21)	(-1.41)	(-1.26)	(0.66)	(1.20)	(0.63)
TrgLEV	-0.07	0.23	-0.11	-0.04	-0.22	-0.47
	(-1.05)	(0.69)	(-1.07)	(-0.28)	(-1.51)	(-1.52)
TrgInstOwn	0.57***	0.84*	0.44***	0.82***	0.19	0.80**
	(6.72)	(1.74)	(3.23)	(5.89)	(1.00)	(2.29)
TrgROA	-0.12*	-0.44*	0.19	0.22*	0.14	-1.10***
	(-1.79)	(-1.84)	(1.39)	(1.82)	(0.75)	(-3.47)
TrgFAGE	-0.10*	-0.18	-0.10	-0.35***	0.32**	-0.31
	(-1.76)	(-0.77)	(-1.02)	(-3.40)	(2.10)	(-1.51)
N of Obs.	2,619	201	953	807	447	211
N of Groups	459	35	164	142	80	38
Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.04	0.20	0.04	0.09	0.05	0.23
Model test *p*-value	0.00	0.09	0.00	0.00	0.04	0.00
Link Test						
p-value of _hat	0.000	0.000	0.000	0.000	0.000	0.000
p-value of _hatsq	0.142	0.387	0.544	0.141	0.902	0.776

Panel B: Wald tests of pairwise differences in the coefficients on *SimQ* across subgroup analyses

Wald test *p*-values are reported.	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
	(3)	(4)	(5)	(6)
(2) Cost efficiency	0.729	0.882	0.448	0.571
(3) Market position		0.671	0.411	0.676
(4) Product portfolio			0.223	0.482
(5) Geo expansion				0.856

Table 20: Alternative Measure of Resource Quality Similarity—Profitability Similarity

Table 20 replicates the analyses of resource quality similarity using an alternative measure that captures profitability similarity (***SimPROF***). ***SimPROF*** is measured as the negative absolute difference in the ratio of net sales minus cost of goods sold and adjusted SG&A expense to net sales. The Compustat item ***XSGA*** is adjusted following Peters and Taylor (2017). Variable definitions are provided in Appendix A.

Panel A presents coefficient estimates from the following conditional logit model with fixed effects at the matched actual-control merger group level. Standard errors are clustered at the same level, and *t*-statistics are reported in parentheses.

$$Deal = \gamma SimPROF + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgRETURN + \beta_4 TrgLEV + \beta_5 TrgINSTOWN + \beta_6 TrgFAGE + GroupFE$$

Panel B presents *p*-values from pairwise Wald tests assessing whether the coefficients on ***SimPROF*** across subgroup analyses in Panel A, columns (2)–(6), differ significantly from one another (i.e., whether their confidence intervals do not overlap).

Panel C presents coefficient estimates examining whether the substitutability of target industry-level resources (or resource quality heterogeneity among potential target firms) moderates the relationship between profitability similarity and merger likelihood. The estimation model is a linear probit with fixed effects at the matched actual-control merger group level, specified as follows. Standard errors are clustered at this level, and *t*-statistics are reported in parentheses.

$$Deal = \alpha + \gamma_1 SimPROF + \gamma_2 SimPROF \times CAT + \beta_1 RelSIZE + \beta_2 TrgSIZE + \beta_3 TrgRETURN + \beta_4 TrgLEV + \beta_5 TrgINSTOWN + \beta_6 TrgFAGE + GroupFE + \varepsilon$$

The columns present coefficient estimates using alternative definitions of ***CAT***, based on alternative measures of resource quality heterogeneity (***ioindPM***, ***ioindPMSD***, or ***ioindHHI***) and alternative indicators for classifying the resource quality heterogeneity levels within the sample (***HIGH*** or ***MOD***). ***HIGH*** equals one if the target firm's industry-level resource quality heterogeneity exceeds the sample median (high level) and zero otherwise (low level). ***MOD*** equals one if the target firm's industry-level resource quality heterogeneity lies within the middle three quintiles of the sample distribution (moderate level) and zero otherwise (tails). One-tailed tests of the coefficients on ***SimPROF*** within each heterogeneity-level subgroup are reported in *italics* in rows highlighted in light grey. Statistically significant coefficients based on one-tailed tests are shown in **bold**, with corresponding *p*-values reported beneath the coefficients.

Panel D presents coefficient estimates for ***SimPROF*** based on the OLS Model (4), analyzing the impact of ***SimPROF*** on shareholder wealth outcomes. Column titles denote the specific shareholder wealth outcome measures. Fixed effects for the acquirer industry and announcement year are included, with standard errors clustered by the same dimensions. *T*-statistics are reported in parentheses. The model is specified as follows.

$$DV = \alpha + \gamma SimPROF + \beta_1 Cash + \beta_2 Stock + \beta_3 Compete + \beta_4 Toehold + \beta_5 Tender + \beta_6 RelDealSize + \beta_7 AcqME + \beta_8 AcqRETURN + \beta_9 AcqLEV + \beta_{10} AccqINSTOWN + \beta_{11} AcqFAGE + \beta_{12} TrgME + \beta_{13} TrgRETURN + \beta_{14} TrgLEV + \beta_{15} TrgINSTOWN + \beta_{16} TrgFAGE + AcqIndFE + YearFE + \varepsilon$$

Panel E reports coefficient estimates for ***SimPROF*** from the OLS Model (6), where the dependent variable is one of three measures of long-run financial performance for mergers, as indicated by cells in the ***DV*** column. Fixed effects for the acquirer industry and announcement year are included. Standard errors clustered by the same dimensions, and *t*-statistics are reported in parentheses.

$$DV = \alpha + \gamma SimPROF + \beta_1 AcqSIZE + \beta_2 AcqRETURN + \beta_3 AcqLEV + \beta_4 AccqINSTOWN + \beta_5 AcqFAGE + \beta_6 TrgSIZE + \beta_7 TrgRETURN + \beta_8 TrgLEV + \beta_9 TrgINSTOWN + \beta_{10} TrgFAGE + AcqIndFE + YearFE + \varepsilon$$

All continuous variables are winsorized at the 1st and 99th percentiles based on the pooled sample and then standardized by subtracting the mean and dividing by the standard deviation of the estimation sample in each analysis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 20, continued

Panel A: Coefficient estimates from adjusted Model (3) using an alternative measure of resource quality similarity—*SimPROF*

	(Pooled sample)	(Cost efficiency)	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
	(1)	(2)	(3)	(4)	(5)	(6)
SimPROF	0.02	-0.08	**4.06*****	0.34	0.70	-0.16
	(0.38)	(-0.48)	**(3.89)**	(1.27)	(1.23)	(-0.67)
RelSIZE	-0.43***	-0.78**	-0.47***	-0.09	-0.62**	-0.55
	(-4.74)	(-2.27)	(-2.92)	(-0.96)	(-2.10)	(-1.52)
TrgSIZE	0.77***	2.67***	0.80*	0.02	0.73	-0.19
	(3.47)	(2.63)	(1.88)	(0.05)	(1.40)	(-0.31)
TrgRETURN	0.01	-0.38	-0.18	0.10	0.16	0.18
	(0.15)	(-1.61)	(-1.41)	(0.93)	(1.12)	(0.82)
TrgLEV	-0.07	0.26	-0.03	-0.03	-0.17	-0.28
	(-1.05)	(0.81)	(-0.25)	(-0.24)	(-1.12)	(-1.12)
TrgInstOwn	0.56***	0.71*	0.49***	0.82***	0.22	0.78**
	(6.63)	(1.69)	(3.52)	(5.96)	(1.20)	(2.05)
TrgFAGE	-0.11**	-0.19	-0.10	-0.32***	0.32**	-0.41**
	(-1.96)	(-0.84)	(-1.05)	(-3.05)	(2.12)	(-2.26)
N of Obs.	2,619	201	953	807	447	211
N of Groups	459	35	164	142	80	38
Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.04	0.17	0.07	0.09	0.06	0.11
Model test *p*-value	0.00	0.09	0.00	0.00	0.02	0.02
Link Test						
p-value of _hat	0.000	0.000	0.000	0.000	0.000	0.001
p-value of _hatsq	0.118	0.830	0.885	0.369	0.923	0.485

Panel B: Wald tests of pairwise differences in the coefficients on *SimPROF* across subgroup analyses

Wald test *p*-values are reported.	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
	(3)	(4)	(5)	(6)
(2) Cost efficiency	0.000	0.181	0.186	0.797
(3) Market position		**0.001**	**0.005**	**0.000**
(4) Product portfolio			0.568	0.161
(5) Geo expansion				0.162

Table 20, continued

Panel C: Moderating effect of target firms' industry-level resource quality heterogeneity on the relationship between *SimPROF* and the likelihood of operating synergy-driven mergers

	ioindPM		ioindPMSD		ioindHHI	
	HIGH	MOD	HIGH	MOD	HIGH	MOD
	(1)	(2)	(3)	(4)	(5)	(6)
SimPROF	-0.00	0.00	0.09*	-0.00	-0.00	0.03
	(-0.09)	(0.16)	(1.71)	(-0.31)	(-0.25)	(1.56)
SimPROF	*-0.00*	*0.00*	***0.09****	*-0.00*	*-0.00*	***0.03****
p-value of one-tailed test	*0.464*	*0.437*	***0.044***	*0.377*	*0.403*	***0.060***
CAT × SimPROF	0.15***	0.00	-0.09*	0.07*	0.02	-0.03
	(3.00)	(0.06)	(-1.71)	(1.95)	(0.88)	(-1.31)
SimPROF + CAT × SimPROF	***0.15*****	*0.00*	*0.00*	***0.07****	*0.02*	*0.00*
p-value of one-tailed test	***0.001***	*0.438*	*0.460*	***0.027***	*0.171*	*0.499*
CAT	(No estimates; absorbed by group fixed effects)					
RelSIZE	-0.06***	-0.07***	-0.07***	-0.06***	-0.06***	-0.06***
	(-4.73)	(-5.14)	(-5.20)	(-4.95)	(-5.07)	(-5.06)
TrgSIZE	0.12***	0.13***	0.13***	0.12***	0.13***	0.13***
	(3.27)	(3.47)	(3.47)	(3.24)	(3.44)	(3.37)
TrgRETURN	-0.00	0.00	0.00	-0.00	0.00	0.00
	(-0.02)	(0.07)	(0.12)	(-0.05)	(0.05)	(0.07)
TrgLEV	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-0.92)	(-1.08)	(-1.10)	(-0.93)	(-1.10)	(-1.06)
TrgINSTOWN	0.09***	0.09***	0.09***	0.09***	0.09***	0.09***
	(7.19)	(7.33)	(7.31)	(7.21)	(7.30)	(7.28)
TrgFAGE	-0.02**	-0.02**	-0.02**	-0.02**	-0.02**	-0.02**
	(-2.19)	(-2.13)	(-2.23)	(-2.22)	(-2.17)	(-2.16)
Intercept	0.16***	0.18***	0.17***	0.17***	0.17***	0.17***
	(41.64)	(147.55)	(37.66)	(56.58)	(247.49)	(153.33)
N of Obs.	2,619	2,619	2,619	2,619	2,619	2,619
N of Groups	459	459	459	459	459	459
Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.02	0.02	0.02	0.02	0.02	0.02
Model test *p*-value	0.00	0.00	0.00	0.00	0.00	0.00

Panel D: Coefficient estimates from Model (4), representing the effect of *SimPROF* on different shareholder wealth outcome measures

	(CGAIN)	(AGAIN)	(ACAR)	(RELTGAIN)	(TCAR)	(TGAIN)
	(1)	(2)	(3)	(4)	(5)	(6)
SimPROF	**-0.32*****	**-0.24****	-0.05	0.05	**-0.18*****	**-0.13****
	(-3.19)	**(-2.45)**	(-1.14)	(1.19)	**(-6.11)**	**(-2.96)**

Panel F: Coefficient estimates from Model (6), representing the effect of *SimPROF* on alternative measures of long-run financial performance of mergers

	DV	Similarity	Coef.	*T* stat.	N of Obs.	Adj. R^2	Controls	AcqInd FE	Year FE
(a)	ΔROA[-1,+1]		**-0.09***	**(-1.81)**	398	0.08	Yes	Yes	Yes
(b)	ΔROA[-1,+2]	SimPROF	**-0.13****	**(-2.23)**	368	0.09	Yes	Yes	Yes
(c)	ΔROA[-2,+2]		**-0.11***	**(-2.11)**	347	0.16	Yes	Yes	Yes

Table 21: Robustness Tests Excluding Vertical Integrations

Table 21 replicates the analyses of target selection and merger performance after excluding vertical integrations from the estimation samples in the corresponding analyses.

Panel A, rows (a)–(c), present coefficient estimates for product similarity (***SimPROD***), geographic proximity (***GeoProx***), and Tobin's Q similarity (***SimQ***) from Models (1), (2), and (3), respectively, analyzing their effects on merger likelihood. Column titles denote distinct estimation samples after excluding groups involving vertical ingestions from the 459 matched actual-control merger groups used in the primary analyses: (1) the pooled sample of operating synergy-driven mergers, (2) the subsample aimed at improving cost efficiency, (3) the subsample aimed at enhancing market position, (4) the subsample motivated by enriching product portfolio, (5) the subsample aimed at expanding into new geographic markets, and (6) the subsample aimed at acquiring innovation resources. Standard errors are clustered at the matched actual-control merger group level, and *t*-statistics are reported in parentheses. The estimation sample comprises 401 horizontal mergers aimed at operating synergies.

Panel B presents coefficient estimates for each interfirm similarity proxy—***SimPROD***, ***GeoProx***, and ***SimQ***—from separate OLS regressions of Model (4), assessing their impact on shareholder wealth outcomes. Column titles represent specific measures of shareholder wealth outcomes. The model includes fixed effects for the acquirer industry and merger announcement year, with standard errors clustered by the same dimensions. *T*-statistics are reported in parentheses. Rows (a)–(c) are estimated based on a sample of 401 mergers, excluding 51 vertical integrations from the original 452 mergers with complete data for shareholder wealth effect analyses. Rows (d)–(f) are estimated based on a sample of 338 mergers, further excluding 63 mergers involving an absolute value of acquirer shareholder cumulative abnormal dollar gains (***AGAIN***) of $1 billion or more. Rows (g)–(i) are estimated based on a sample of 309 mergers, further excluding 29 mergers involving an absolute value of ***AGAIN*** of $500 million or more and less than $1 billion.

OLS Model (5) is estimated separately for each interfirm similarity proxy—***SimPROD***, ***GeoProx***, and ***SimQ***—to assess their impact on shareholder wealth outcomes across subsamples driven by distinct value-creation motives. The model includes fixed effects for the acquirer industry and merger announcement year, with standard errors clustered by the same dimensions. **Panel C** presents only statistically significant coefficient estimates for the similarity proxies within each value-creation motive subgroup, based on Wald tests of linear combinations of the baseline subgroup coefficient and the corresponding interaction term from Model (5) coefficient estimates, with *p*-values reported beneath the (combined) coefficients. Column titles represent specific shareholder wealth outcome measures. The estimation sample comprises 401 horizontal mergers aimed at operating synergies.

All continuous variables are winsorized at the 1st and 99th percentiles based on the pooled sample and then standardized by subtracting the mean and dividing by the standard deviation of the estimation sample in each analysis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Coefficient estimates for *SimPROD*, *GeoProx*, and *SimQ* from Models (1), (2), and (3), respectively

		(Pooled sample)	(Cost efficiency)	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
		(1)	(2)	(3)	(4)	(5)	(6)
(a)	SimPROD	**2.17*** **	**2.50*** **	**1.80*** **	**1.99*** **	**1.60*** **	**2.75*** **
		(14.28)	**(3.36)**	**(8.21)**	**(7.92)**	**(5.19)**	**(4.87)**
(b)	GeoProx	**0.81*** **	**0.73*** **	**1.26*** **	**0.45*** **	**1.45*** **	0.15
		(11.10)	**(2.58)**	**(8.15)**	**(4.09)**	**(5.08)**	(0.64)
(c)	SimQ	**0.20** **	-0.16	0.08	**0.38*** **	0.06	**0.53***
		(2.42)	(-0.38)	(0.65)	**(2.67)**	(0.43)	**(1.66)**
N of Obs.		2,315	165	865	656	435	194
N of Groups		407	29	149	116	78	35

Table 21, continued

Panel B: Coefficient estimates from Model (4), analyzing the effect of product similarity (*SimPROD*), geographic proximity (*GeoProx*), and Tobin's Q similarity (*SimQ*) on shareholder wealth outcomes, separately

		(CGAIN)	(AGAIN)	(ACAR)	(RELTGAIN)	(TCAR)	(TGAIN)
		(1)	(2)	(3)	(4)	(5)	(6)
(a)	SimPROD	0.12	**0.07*** **	**0.14*** **	**-0.14***	-0.07	0.05
		(1.42)	**(3.39)**	**(3.98)**	**(-2.13)**	(-0.95)	(0.58)
(b)	GeoProx	0.03	0.02	0.04	-0.02	-0.02	0.04
		(0.82)	(0.43)	(0.80)	(-0.24)	(-0.40)	(1.25)
(c)	SimQ	0.06	0.06	0.13	-0.00	-0.09	-0.02
		(1.25)	(1.54)	(1.70)	(-0.07)	(-1.64)	(-0.34)
	Exclude deals where AGAIN >= $1 billion						
(d)	SimPROD	-0.05	0.05	**0.09** **	**-0.14***	-0.08	**-0.10*** **
		(-0.83)	(0.80)	**(2.40)**	**(-1.99)**	(-1.07)	**(-3.97)**
(e)	GeoProx	0.02	0.05	0.00	0.01	-0.00	-0.02
		(0.34)	(0.87)	(0.07)	(0.13)	(-0.01)	(-0.38)
(f)	SimQ	0.09	0.14	0.13	0.04	-0.09	-0.02
		(1.01)	(1.11)	(1.36)	(0.55)	(-1.10)	(-0.18)
	Exclude deals where AGAIN >= $500 million						
(g)	SimPROD	-0.02	0.05	0.09	-0.14	-0.09	-0.06
		(-0.47)	(0.76)	(1.73)	(-1.58)	(-1.12)	(-0.90)
(h)	GeoProx	0.04	0.05	-0.02	0.04	-0.01	0.02
		(0.65)	(0.70)	(-0.27)	(0.48)	(-0.21)	(0.33)
(i)	SimQ	0.07	**0.12***	0.16	0.06	-0.10	-0.00
		(1.09)	**(1.85)**	(1.58)	(0.77)	(-0.97)	(-0.05)

Panel C: Statistically significant coefficients for similarity proxies within distinct value-creation motive subgroups, derived from coefficient estimates from Model (5)

		(CGAIN)	(AGAIN)	(ACAR)	(RELTGAIN)	(TCAR)	(TGAIN)
		(1)	(2)	(3)	(4)	(5)	(6)
(a)	Model (5): Similarity = SimPROD						
	Improve cost efficiency	**0.28*** **	**0.45*** **				
		0.010	**0.005**				
	Enhance market position						**-0.17** **
							0.026
	Geographic expansion			**0.31** **	**-0.29** **	**-0.26*** **	
				0.010	**0.024**	**0.003**	
	Acquire innovation resources	**-1.24** **		**-0.52***			**-0.95*** **
		0.014		**0.085**			**0.007**
(b)	Model (5): Similarity = GeoProx						
	Improve cost efficiency	**-0.16***	**-0.20***				
		0.089	**0.057**				
	Acquire innovation resources			**-0.28***			**-0.52***
				0.089			**0.078**
(c)	Model (5): Similarity = SimQ						
	Geographic expansion					**-0.24***	
						0.057	
	Acquire innovation resources				**-0.29***		**0.04** **
					0.064		**0.026**

Table 22: Robustness Tests Excluding Mergers with Extreme Deal Price Premiums

Table 22 replicates the analyses of target selection and merger performance after excluding mergers with extreme deal price premiums (larger than two or less than zero) from the estimation samples in the corresponding analyses.

Panel A, rows (a)–(c), present coefficient estimates for product similarity (***SimPROD***), geographic proximity (***GeoProx***), and resource quality similarity (***SimQ***) from Models (1), (2), and (3), respectively, analyzing their effects on merger likelihood. Column titles denote distinct estimation samples after retaining only mergers with price premiums between zero and two: (1) the pooled sample of operating synergy-driven mergers, (2) the subsample aimed at improving cost efficiency, (3) the subsample aimed at enhancing market position, (4) the subsample motivated by enriching product portfolio, (5) the subsample aimed at expanding into new geographic markets, and (6) the subsample aimed at acquiring innovation resources. Standard errors are clustered at the matched actual-control merger group level, and *t*-statistics are reported in parentheses. The estimation sample comprises 407 operating synergy-driven mergers with price premiums between zero and two.

Panel B presents coefficient estimates for each interfirm similarity proxy from separate OLS regressions of Model (4), examining their impact on shareholder wealth outcomes. Column titles indicate specific shareholder wealth outcome measures. The model includes fixed effects for the acquirer industry and merger announcement year. Standard errors clustered by the same dimensions, and *t*-statistics are reported in parentheses. Rows (a)–(c) are estimated based on a sample of 407 mergers, excluding 45 deals involving extreme price premiums from the 452 mergers with complete data for shareholder wealth effect analyses. Rows (d)–(f) are estimated based on a sample of 337 mergers, further excluding 70 mergers with an absolute value of acquirer shareholder cumulative abnormal dollar gains (***AGAIN***) of $1 billion or more. Rows (g)–(i) are estimated based on a sample of 305 mergers, further excluding 32 mergers with an absolute value of ***AGAIN*** of $500 million or more and less than $1 billion.

OLS Model (5) is estimated separately for each interfirm similarity proxy—***SimPROD***, ***GeoProx***, and ***SimQ***—to assess their impact on shareholder wealth outcomes across subsamples driven by distinct value-creation motives. The model includes fixed effects for the acquirer industry and merger announcement year, with standard errors clustered by the same dimensions. **Panel C** presents only statistically significant coefficient estimates for the similarity proxy within each value-creation motive subgroup, based on Wald tests of linear combinations of the baseline subgroup coefficient and the corresponding interaction term from Model (5) coefficient estimates. Wald test *p*-values are reported beneath the (linearly combined) coefficients. Column titles represent the specific shareholder wealth outcome measures. The estimation sample comprises 407 operating synergy-driven mergers with price premiums between zero and two.

All continuous variables are winsorized at the 1st and 99th percentiles based on the relevant pooled sample. These variables are then standardized by subtracting the mean and dividing by the standard deviation of the estimation sample in each analysis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Coefficient estimates for *SimPROD*, *GeoProx*, and *SimQ* from Models (1), (2), and (3), respectively

		(Pooled sample)	(Cost efficiency)	(Market position)	(Product portfolio)	(Geo expansion)	(Innovation resources)
		(1)	(2)	(3)	(4)	(5)	(6)
(a)	SimPROD	**2.30*** **	**3.07*** **	**2.09*** **	**1.86*** **	**1.88*** **	**2.35*** **
		(14.52)	**(3.49)**	**(8.58)**	**(8.12)**	**(5.01)**	**(4.72)**
(b)	GeoProx	**0.77*** **	**0.85*** **	**1.14*** **	**0.47*** **	**1.38*** **	0.18
		(11.14)	**(2.71)**	**(8.13)**	**(4.70)**	**(4.85)**	(0.73)
(c)	SimQ	**0.22*** **	0.05	**0.27** **	**0.29** **	-0.10	**0.64** **
		(2.85)	(0.13)	**(2.25)**	**(2.47)**	(-0.64)	**(2.32)**
N of Obs.		2,321	180	819	757	389	176
N of Groups		407	31	141	133	70	32

Table 22, continued

Panel B: Coefficient estimates from Model (4) for *SimPROD*, *GeoProx*, and *SimQ*, separately

		(CGAIN)	(AGAIN)	(ACAR)	(RELTGAIN)	(TCAR)	(TGAIN)
		(1)	(2)	(3)	(4)	(5)	(6)
(a)	SimPROD	0.16	0.08	**0.18****	**-0.10***	-0.05	0.08
		(1.19)	(1.40)	**(2.91)**	**(-1.85)**	(-0.76)	(0.75)
(b)	GeoProx	0.02[1]	-0.01	0.03	0.02	-0.05	0.05
			(-0.14)	(0.58)	(0.30)	(-0.82)	(1.35)
(c)	SimQ	**0.09***	**0.09***	0.11[2]	-0.04	-0.06	-0.01
		(2.02)	**(2.15)**		(-0.44)	(-1.04)	(-0.25)
	Exclude deals where AGAIN >= $1 billion						
(d)	SimPROD	0.04	0.12	**0.17****	-0.10	-0.07	-0.05
		(0.33)	(1.39)	**(2.23)**	(-1.27)	(-1.07)	(-0.51)
(e)	GeoProx	0.00	0.02	0.00	0.06	-0.01	-0.02
		(0.02)	(0.28)	(0.04)	(0.70)	(-0.27)	(-0.34)
(f)	SimQ	0.12	0.14	0.08	0.00	-0.07	0.05
		(1.71)	(1.36)	(1.31)	(0.02)	(-1.07)	(0.95)
	Exclude deals where AGAIN >= $500 million						
(g)	SimPROD	0.04	0.07	**0.14***	-0.06	-0.07	0.01
		(0.47)	(0.72)	**(2.05)**	(-0.74)	(-1.02)	(0.06)
(h)	GeoProx	0.04	-0.00	-0.01	0.10	-0.03	0.05
		(0.92)	(-0.01)	(-0.16)	(1.20)	(-0.42)	(0.85)
(i)	SimQ	**0.14****	**0.13***	**0.12***	-0.00	-0.09	0.09
		(2.31)	**(2.20)**	**(1.90)**	(-0.06)	(-1.04)	(1.66)

Panel C: Statistically significant coefficients for similarity proxies within specific value-creation motive subgroups

		(CGAIN)	(AGAIN)	(ACAR)	(RELTGAIN)	(TCAR)	(TGAIN)
		(1)	(2)	(3)	(4)	(5)	(6)
(a)	Model (5): Similarity = SimPROD						
	Improve cost efficiency	**0.36***	**0.45***	**0.29***			
		0.055	**0.066**	**0.074**			
	Geographic expansion					**-0.32***	
						0.063	
	Acquire innovation resources						**-0.82***
							0.077
(c)	Model (5): Similarity = SimQ						
	Improve cost efficiency			**0.36***			
				0.052			
	Enrich product portfolio	**0.29***	**0.19***	**0.21***			
		0.083	**0.089**	**0.064**			
	Geographic expansion					**0.08****	
						0.047	
	Acquire innovation resources				**-0.35***		
					0.089		

[1] To resolve estimation issues involving missing standard errors, I exclude the dummy variable ***Toehold***, which applies to three observations. The coefficient is statistically insignificant.

[2] Excluding the dummy variable ***Compete***, which applies to twelve observations, resolves the issue of missing standard error estimations in this model. The coefficient is statistically insignificant.