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Does motivation for M&A depend on the stage of the economic cycle?

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Abstract

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This thesis explores *why* firms engage in M&A, focusing on their changes across the economic cycle. The authors adopt a behavioural lens to categorise M&A motivations into four empirically derived profiles to analyse one of the largest recent database.

An analysis of tech-sector deals on a new dataset further examines the role of geographic proximity and tech industry behaviour towards M&A under different macro regimes. By connecting micro-strategy with macroeconomic context, the thesis advances the empirical framework to understand the "why" behind M&A.

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1. Introduction

Mergers and acquisitions have driven corporate growth since the 1800s. Think of any merger wave from the dot-com era to the current AI boom; their relevance varies with the economic cycle and the time we are in. Usually, we expect periods of significant economic expansion and growth to have a high volume of deals as opposed to downturns when fewer deals turn up. This cycle-specific behaviour and its strong association with the macro environment lead to the premise of this research. We want to answer "the Why" of deal making, how it shifts across cycles, what behavioural patterns do they exhibit, and we will want to explore in greater detail how the macro, micro and deal relevant characteristics interact.

1.1 Research Question and Rationale

This section is meant to build the core questions which we will answer in this research, building upon the "common sense" logic of deal-making. The objective is to determine whether firms' reasons for engaging in M&A vary between expansions (booms) and contractions (recessions) periods, and go deeper into how the motivations are then shaped based on the prevailing macro environment. The researchers focus on a cross-industry sample initially to capture broad patterns across decades and then go into an in-depth overview of the tech industry to uncover motivation for deal-making in the industry, which is notoriously famous for "absurd deals".

The rationale for this research is threefold: First, M&A activity is known to be cyclical, clustering in "merger waves" that often coincide with high-growth, high-valuation periods, as can be seen in the recent 2021-2022 period. We want to understand if the underlying motives of deals differ in hot markets versus downturns, and if it can shed light on whether booms encourage value-creating synergistic combinations. Second, the success rate of M&A deals is low; a lot of studies find that a large proportion (often 50-60%) of acquisitions fail to create long-term value for the acquirer's shareholders (King *et al.*, 2004; Haleblian *et al.*, 2009). If these post-deal outcomes are significant and show systematic differences over the economic cycle, e.g. deals in recession fare because they are reasonably priced, it will generate important results for corporate strategy with regard to timing. We already observe such behaviour in the latest Darktrace deal and Hess's oilfield acquisitions. Third, by examining cross-cycle variation across decades of data, this research bridges macroeconomic conditions with micro-level corporate decision-making.

This study emphasises the first and third rationales, while the second is left for later research. This is because we are more inclined to answer the "why aspect" of the deal, something that occurs pre-merger and not on “what happened later”, which is an extensive study in itself; however, we do explore this when looking at real-world deals in the case study section.

1.2 Contribution to Literature

Our thesis contributes to the M&A literature by linking macroeconomic conditions with firm-level and deal-level behaviour. While prior literature has documented the existence of merger waves (Gort, 1969; Martynova & Renneboog, 2008) and explored various theories for corporate merger motivations (neoclassical vs. behavioral approach), this will be one of the few studies that is mapping motivation types to economic cycle phases, studies them in various contexts and economic rationale and also uses large scale data for empirical testing.

The authors’ study integrates multiple perspectives:

- From corporate finance, the study examines how deal decisions are influenced by corporate strategy constraints like capital, wrong valuation or agency problems (Jensen, 1986; Baker & Wurgler, 2002)
- From industrial organisation, deal activity is related to industrial advancements, restructuring needs during different curves of the economic cycle, and defensive industrial entry across cycles (Mitchell & Mulherin, 1996)
- From empirical M&A research, we extend studies such as Harford (2005) and Alexandridis et al. (2017), using deal-level characteristics (e.g., relatedness, financing method, innovation), using a unique and innovative taxonomy and segregation of deal motivation for the first time into an empirical framework

1.2.1 Gaps in the literature

The literature on M&A waves and motivations is quite extensive; however, several important gaps still exist. First, much empirical research focuses on overall deal volume and explores the “what” of the deal rather than motivation changes across the cycles (Harford, 2005; Martynova & Renneboog, 2008). Second, the macroeconomic relations across economic factors like GDP growth, market sentiments, and firm-level decision making are not explored in a behavioural context (Jovanovic & Rousseau, 2002; Shleifer & Vishny, 2003). Third, it is believed that innovation is low or declines in a recession; however, M&A as an alternative to in-house R&D with the acquisition of innovative startups has received little empirical investigation(Phillips & Zhdanov, 2013; Ding & Hemingway, 2024). Finally, contagion effects and herding behaviour among firms during boom periods, “merger waves”, as well as cross-border differences in deal timing, are acknowledged in theory but rarely tested empirically (Ahern & Harford, 2014; Yang, 2024).

This thesis aims to address these gaps by empirically examining how the motivations for M&A transactions vary across a large cross-industry dataset. The research also explores in depth the motivational factors that influence the tech industry and how deal strategy and behaviour changes across the industry by breaking into a unique framework of 4 distinct profiles for the first time in M&A literature. With the growth of machine learning, a lot more can be achieved to check for biases and arbitrary statistical errors, something that was not available to the previous set of researchers and has been explored in the thesis.

2. Literature review

2.1 Merger Waves and the Cyclical Nature of M&A Activity

Mergers and acquisition activity is known to occur in a herd, that align with periods of economic expansion, which is identified by higher valuations, ease of liquidity availability, and investor optimism (Harford, 2005; Mitchell & Mulherin, 1996). These factors, get reversed in the downward flow of the economic cycle, leading to lesser deal-making (both by deal size and number of deals) in a downward-cycle. Harford (2005) explains that economic or regulatory shocks can trigger consolidation, but a merger wave is closely aligned with capital liquidity, i.e. if sufficient credit supply is available to make the deal possible. This procyclical pattern is well-established in both industry-specific and cross-sector studies conducted by economists (Eisenbarth & Meckl, 2014; Rhodes-Kropf et al., 2005).

One possible explanation might be the neoclassical theory of mergers. This theory suggests that external shocks, such as deregulation and technological change, drive companies to restructure. They aim to improve efficiency for future challenges. Mergers and acquisitions often facilitate this process (Mitchell & Mulherin, 1996).
However, a shock alone is not sufficient - abundant capital liquidity (easy financing, high stock prices, credit from financial sponsors, etc.) is required to ease the flow of capital and make it a “merger wave”. With inflated equity valuations and cheap credit availability, firms have the required financing to pursue acquisitions, which results in clusters of deal-making as opposed to an even distribution across time.

- *For example, Jarrad Harford (2005) documents that industry merger waves occur when a triggering shock coincides with high liquidity; in contrast, “market timing” variables (misvaluation alone) have limited power in explaining waves.* Macro financial activity is crucial in not just corporate decision-making but also aligning the “corporate agents” with financial motives required to make the deal go through, both from the target and the acquirer’s perspective.

Competitive dynamics and peer behaviour also serve as a driver for deal-making. Firms often follow their peers: if one company in an industry starts acquiring, rivals feel pressure to make their own acquisitions for fear of falling behind. This “peer effect” can propagate not just through but across industries to give rise to a merger wave. Ahern & Harford (2014) find that peer influence in M&A can spread even beyond local markets, helping to form the well-documented pattern of clustered M&A events. This underscores the role of herd behaviour in fueling merger waves, especially during boom periods when many firms simultaneously chase growth (observable during the 2000s merger wave).

Historically, merger waves have occurred during periods of economic optimism and managerial overconfidence:

- The late 1990s dot-com boom saw a wave of tech and telecom acquisitions fueled by high stock valuations and high growth expectations, many of which never materialised significantly for the acquirer to benefit from
- Conversely, the 1980s wave (especially hostile takeovers) is often credited with more discipline and efficiency gains (e.g. breaking up conglomerates), implying some waves can be more value-driven.

In line with this approach, M&A volume typically falls in recessions, “the troughs of the cycle”, due to tighter financing, cautious managerial strategy and governmental surveillance.

2.2 Drivers of merger waves: Strategic synergies vs. Behavioural biases

As stated in the introduction, the literature often classifies M&A motivations into strategic (typically termed as “value-creating” synergistic deals) and behavioural motives (stemming from managerial bases, often “value-destroying”) categories. Strategic motives stand out more during an industry shock, and it can offer a strong reason for consolidation (Lambrecht, 2004; Maksimovic & Phillips, 2001). However, behavioral theories like the hubris hypothesis (Roll, 1986) suggest that managerial overconfidence and herd behavior are the main factors behind inefficient acquisitions that do not tend to do well when looked from a future perspective. Jensen (1986) also links free cash flow to inefficient empire-building in late-cycle booms (this is seen quite recently with the AI-powered deal-making with big tech, having cash from the recent tech boom being plundered on AI native companies).

Shleifer and Vishny (2003) advance the misvaluation theory, proposing that overvalued acquirers use their stock as currency to buy “less valued” targets. Rhodes-Kropf et al. (2005) support this through their research paper in an empirical fashion. They show that market-to-book ratios of acquirers exceed those of targets in merger waves. Misvaluation often acts as a strong driver for both the acquirer and the target as a motivation to make deals.

2.3 Deal Motives and Performance in Boom vs. Bust Periods

Acquirers and target companies have different characteristic across economic cycles, the boom and the bust cycles. During booms or upwards economic cycles, deals are larger, stock-financed, and often driven by growth and expansion motives. During downturns, deals tend to be opportunistic, targeting distressed or “discounted” firms (Ding & Hemingway, 2024). This section explored these variations. We have organised this into two different sections.

2.3.1. Economic boom Periods (High-growth and high-valuation markets):

During economic expansions and bull markets, firms face strong growth prospects, high investor expectations, and often have highly valued stock to use for acquisition financing. Several theories and findings characterise these deals and serve to identify motives:

- Market-driven overvaluation motives: Shleifer & Vishny (2003) state that many acquisitions in booms are “stock market driven”, meaning acquirers use their overvalued stock to buy other firms. Mergers are seen to occur without any genuine synergies in such a chase with the acquirer’s highly valued stocks as a cheap financing method to buy tangible assets off the balance sheet of the target. This situation often leads to a win-win scenario (since the target company gets a premium and the acquirers’ shareholders exploit the stock overvaluation to their advantage), but this is usually not value-creating in the long term. Shleifer and Vishny have noted that while the 1980s takeover wave likely had efficiency gains, “the wave of acquisitions in the 1990s might have destroyed value” due to “happy-market” conditions. In general, evidence shows that acquisitions by “glamour” firms (with high market-to-book ratios) significantly result in underperformance in the long run, whereas acquisitions by low-valuation “value” firms are better for the shareholders. Rau and Vermaelen (1998) document this pattern: high-valuation acquirers earned negative abnormal returns post-merger. This is consistent with the idea that boom-time deals do not rely on solid fundamentals but are driven by overoptimistic or overconfident management and investor hype.
- Overconfidence: Roll’s hubris hypothesis states that some CEOs engage in mergers due to overconfidence in their ability to extract value, paying too much for targets (a

tendency aggravated in boom markets with a general sense of optimism in the markets). Empirical work supports this; Malmendier & Tate (2008) find that overconfident CEOs are more likely to do acquisitions, especially using free cash flows and internal funds, leading to squander, often destroying shareholder value as a result. Misinterpretation of strong market times as validation of the CEO's own ability leads to an increase in overconfidence-driven deals, which tend to rise in good times, driven by empire-building behaviour. Such deals may show positive announcement returns (markets initially cheer growth plans) but weaker long-term performance, reflecting overpayment (often in the form of a decline in stock performance later as the market cools down). A European study by Cardinali and Wikrén (2012) found that acquisitions made during high market valuation periods had significantly higher announcement returns than those in low-valuation periods. However, in aggregate, they yielded negative long-term returns. The authors suggest that in boom periods, acquirers often overpay under the influence of bullish sentiment, typically also supported by their investors.

- Fads: During booms, firms may also pursue M&A to ride the wave of a "must-expand at all costs" fad. If everyone is acquiring, boards may pressure CEOs not to be left out and sometimes may also question their ability to recognise opportunistic deal times. This can lead to acquisitions motivated by a "growth at any cost" mentality. Such patterns were prevalent in sectors like telecommunications in the late 1990s and banking in the mid-2000s. These deals often lacked careful strategic rationale and ended poorly when the cycle turned, as is the case with most fear-driven behaviour. Research on peer effects substantiates the fact that many boom-time acquisitions are reactive, and not a purely proactive strategy. Models by Yang (2024) showcase the herding effect in recent times, with competitive pressure within industries making firms more likely to acquire during booms.
- Cheap capital and payment method: High-liquidity booms also shift how deals are financed and structured. In bull markets, stock-financed acquisitions increase (acquirers capitalise on high share prices, as stated before). However, we also see more leveraged buyouts and debt-financed deals since credit is abundant (e.g. the junk bond-fueled wave of the 1980s or the recent 2020). The choices firms make with regards to their capital structures can lead to stakeholder management and agency problems: stock deals concentrate risk on target shareholders if the acquirer's price later falls, and heavy debt from LBOs can become unsustainable in a downturn (with interest coverage and default risks). LBO-focused deals made in the early 2010s are

being seen to collapse in the heavy interest rate environment post-2021, with distressed sales being common, with firms unable to service their debts or interests.

- Net outcome in booms: The picture that emerges is mixed. Boom-time M&A can enable strategic combinations in growing markets, but it also encourages excess amongst strong optimism and biases. On average, empirical evidence shows that over-optimism and over-payment dominate. Researchers (Bouwman, Fuller &Nain, 2009) found that even though European boom acquisitions were looking good at announcement, "*all portfolios (high, low, neutral valuation periods) ultimately had significantly negative long-term returns*." Rahaman (2014) found that firms which were "hyperactive bidders" in expansionary periods, as compared to more disciplined firms, had a higher chance of financial distress or exit in the subsequent recession. A deal-making spree during the good times can overextend a firm's ability to sustain itself in the long run; they may over-leverage or mismanage integration, leaving them vulnerable and over-exposed to macro-shocks when the cycle turns.

2.3.2. Downturns and Recessions:

In economic downturns, far fewer deals happen, but those that do tend to reflect different motivations and profiles from the up-trend:

- "Fire-Sale" opportunities: Warren Buffett, in his annual letters to shareholders, suggests that recessions can create bargain buying opportunities where healthy firms with strong balance sheets can acquire valuable assets or technologies from distressed targets "at a discount", a strategy he employed at Berkshire. Ziran Ding and Benjamin Hemingway (2024) provide empirical support for this: "During *recessions, M&A targets are in significantly worse financial health but have higher innovation levels compared to targets in booms".* Downward deal markets typically see larger, more profitable and stronger acquirers, on the other hand. This indicates that cash-rich market leaders "shop" for innovative but cash-starved companies when valuations are low, consistent with a value-oriented motivation. This results in a synergistic combination such that the acquirer gains technology or assets which complement its business, and the target's projects get cash flow to operate and survive. These deals show value-creation such that the acquirer is disciplining underutilised assets (efficient resource allocation associated with Adam Smith's invisible hand (Smith, 1776). This also suggests antitrust policy might consider a more lenient stance in recessions to allow such efficiency-enhancing deals.
- Strategic refocusing vs. diversification: In downturns, companies are more risk-averse and capital is scarce. Firms are forced only to pursue acquisitions that fit their

strategic needs (e.g. consolidating a core market, or acquiring a technology that's crucial for future competitiveness, etc.). Market-based, expansive, and diversifying conglomerate-style mergers are less common, with less appetite for them in the market. Instead, we often see "bolt-on" acquisitions, that is, smaller deals that fill a gap in the acquirer's capabilities at a discounted price. These deals tend to have more apparent synergistic rationale and are forced by the market to be more disciplined in valuation due to capital constraints. Research finds that firms engage in M&A during downturns as a necessity or survival strategy, mainly from the target's point of view.

- Innovation-Driven Motives: An interesting pattern is that the use of M&A is to buy innovation when internal R&D is tough. In recessions, firms often cut R&D and capital expenditures to conserve cash and focus on their core business, which can hurt innovation. Strong firms may choose to acquire innovative startups or competitors as a strong driver when the markets improve. A study by Ding & Hemingway (2024) highlights that larger companies are more interested in buying smaller companies (usually at a bargain price) during downturns (more pronounced as compared to upward market trends) with innovation as their main driver. This aligns with theories by Phillips and Zhdanov (2013), who model how a functioning M&A market actually encourages innovation by small firms; if a startup knows a larger company might buy it out, that exit option motivates the startup to invest in R&D, thus fuelling growth. In boom times, small firms can get cheap funding or go public, but in recessions, acquisition becomes a key exit path. This acts like an "insurance" for innovation that might otherwise die for lack of capital. Large firms may prefer acquisitions over risky in-house R&D during uncertain periods and due to a lack of budget for non-core business activities. This dynamic can reverse depending on the cycle; in a booming economy with abundant venture capital, a small tech firm might stay independent longer. This way, economic cycles influence the choice between "make or buy" innovation.

Eisenbarth and Meckl (2014) find that "market trough deals" outperform boom ones in the long term. In contrast, not all downturn acquisitions succeed; Ang and Mauck (2010) warn that *"despite the narrative of 'firesale discounts,' higher premiums are seen to be offered to distressed targets in downturns; acquirer announcement returns hence, remain negative on average"*.

2.4 Macro-economic and micro-economic linkages

Understanding mergers through an economic cycle-based lens bridges macroeconomic trends with firm-level decision-making (This is how we establish later in the text “the context” of deal making with resepct to its environment). Downturns limit mergers to strategic buyers as opposed to economic booms that facilitate expansionary acquisitions (Harford, 2005; Shleifer & Vishny, 2003).

The literature we studied highlighted the role of timing the market done by the manager and the board, market sentiment, and financing ability in shaping merger outcomes. “Market trough” acquisitions often generate superior long-term returns. Literature suggests that firm strategy and acquisition should be aligned with macro conditions, focusing on discipline during booms and opportunism during busts (Bouwman et al., 2009; Eisenbarth & Meckl, 2014).

Policy implications also arise (we have discussed it extensively in the technological sector analysis in our text below). Regulators might adopt a more lenient stance during downturns (due to efficiency driven corporate mindset) to facilitate value-driven consolidations while imposing greater scrutiny during booms to counter speculations (Bai & Zhang, 2024). This is also increased with a more sceptical view of monopolistic tendencies in big firms during the two phases of the economic cycle.

2.4.1 Synergy vs. excess: value creation/value-hallucination in the cycle

M&A deals in theoretical literature are classified as being driven by genuine value creation (synergies) or by managerial biases and market mispricing (hubris/excess). The prevalence of these motives swings with the economic cycle:

- In boom markets, as discussed, excess-driven deals become more common. High valuations and positive sentiment can convince managers and investors that “this time is different” and that expansive acquisitions will create tremendous growth, even when objective analysis might be less optimistic. Overestimated projected synergies with high adoption rate dominate this time period, with bankers pushing dealflow based on “quick realisation” potential. Roll (1986) proves in their empirical study that takeover booms, bidders often erroneously believe their management can extract more value from targets than others could, which leads to overbidding (driven by overconfidence). This is rather enhanced by the feedback loop of a rising market which works in a cyclical fashion: rising stock prices serve as a proxy to validate correct decision-making which in turn enforces more of such decisions driven by over-enthusiastic management. Investor sentiment also plays a role; during booms, markets may initially reward acquirers (with stock price rise on merger news, simply because of ubiquitous capital availability), reinforcing managerial belief that the deal was “correct”, even if long-run performance tells another story. Academic surveys have found that many acquisitions destroy shareholder value on average, particularly those undertaken at the height of market cycles when valuations are inflated and managerial discipline is weakest (Meckl & Röhrle, 2016; Moeller & Schlingemann,2020; Stulz, 2004; King et al., 2004).

- In downturns, there is a reversion to corporate finance fundamentals. Deals are more likely driven by synergy and necessity: a company will buy another only if there is a clear value proposition, e.g. cost savings through consolidation, securing a key technology, or picking up assets at discounted prices. Because of a weak environment (e.g. declining profits, cautious investors), the excess is also less. Research finds that fewer “bad” acquisitions occur in recessions, partly because overvalued equity is unavailable as a means of financing, and CEOs cannot easily fool themselves or others when markets are pessimistic. Longitudinal studies over multiple cycles conclude that firms which time their M&A strategy to be more balanced, not solely loading up during peaks, tend to be more resilient.

The M&A motivation literature (e.g. Martynova & Renneboog, 2008) notes that every merger wave in history had a different character, which is some more driven by technological synergies (e.g. early 1900s and 1990s waves), others by financial engineering and misvaluation (1960s conglomerate wave, late 1980s LBO wave, etc.).

2.4.2 Macro-economic conditions and micro-level M&A decisions

Connecting these threads is the recognition that macroeconomic conditions strongly shape micro-level corporate decisions on acquisitions. Several linkages which we discuss below illustrate this bridge between macro and micro:

- Valuation and sentiment: Broad market valuations (often measured by aggregate P/E or market-to-book ratios) make it easier for corporates to start potential deal making. In high valuation bull markets, companies with high stock prices find it cheaper to pay with shares, and targets are more willing to accept stock offers, resulting in more deals. Executives feel pressure to make bold moves (like transformative acquisitions) because of high valuations, which for investors translates to high expectations for growth. In contrast, bold valuations are punished by the markets during bear markets. Investor scepticism makes stock a less attractive currency and also makes CEOs hesitant to issue undervalued equity for acquisitions (share price dilution concerns). This means the bar for deals is higher in downturns, leading to fewer but more sensible transactions.

- Financing conditions: Interest rates and credit availability are macro factors that directly impact deal financing feasibility. In loose monetary conditions with low interest rates (often accompanying booms), debt-financed takeovers surge because the cost of borrowing is low and the central bank is trying to ease and grow the economy, taking a dovish stance. This was evident in multiple waves; for example, cheap credit in 2004-2007 fueled a private equity buyout boom. As opposed to this, in a credit crunch with tight credit conditions or high interest rates, highly leveraged deals dry up. Firms with substantial cash reserves gain a relative advantage in such times, as they can do all cash deals when others cannot, allowing them to cherry-pick targets, as observed in the significant tech-powered AI acquisitions. When liquidity dries up (e.g. after a financial crisis), deal volume falls.
- Economic outlook and corporate strategy: Firms often aim to expand market share or enter new markets during robust GDP growth and low unemployment (boom). A merger is a fast way to do so, and it fits the expansionary corporate strategy. During recessions, strategy shifts to efficiency, profitability and core business focus; sometimes, companies may even divest non-core divisions. Any acquisitions in this time are likely to be those that help cut costs (e.g. acquiring a competitor to realise economies of scale) or reposition for the post-recession environment with increased capability. For instance, if a recession accelerates an industry shakeout, a firm might acquire a distressed rival to emerge as a stronger player when growth returns. Macro conditions are intertwined with micro and firm level decision making process. Recessions act as a catalyst to consolidation, fueling rivalries over who will buy and at what price. A recent study on Chinese firms (Bai & Zhang, 2024) found that acquisitions generally enhanced long-term innovation and efficiency for the acquiring firms. They suggest that during economic downturns, firms leverage deals to restructure and innovate, taking advantage of slack in the market to position for future growth.
- Cross-border considerations: An additional layer is that boom vs. recession markets are not always synchronised globally, driven by local geopolitics and currency dynamics. Sometimes a boom in one region coincides with a slump elsewhere, leading to cross-border deal flows (firms in stronger economies acquiring assets in weaker economies). For example, U.S. or European companies often went bargain-hunting in Asia during the late 1990s Asian Financial Crisis. This arbitrage is another way macro factors drive who buys whom. A European study by Cardinali & Wikrén (2012) also noted that Europe's high valuation periods often involved many cross-

border deals, which come with extra complexities underlying risk during the boom phase, and weaker announcement-day returns.

2.4.3 Literature review on tech deals and innovation

An acquisition deal in tech is usually motivated by acquiring new technologies or capabilities. The tech sector provides a microcosm of the cycle dynamics, as is shown by the literature below:

- Innovation vs. integration trade-off: Cloodt, Hagedoorn & Van Kranenburg (2006) studied high-tech acquisitions and found a nuanced outcome, that acquiring another tech firm can boost the combined firm's innovation output in the short term, but the effect often reverses in the long term. They found a negative impact on innovation in non-technological acquisitions (e.g. a high-tech firm buying an unrelated business), this is also a concept we deal with in depth during our technical analyses and highlighted in the case study of AOL. The long-run fade was explained by integration challenges and possibly the acquirer's inability to harness the acquired R&D potential fully. They also discovered that the acquisitions of targets with either *too similar* or *too distant* technologies can hurt innovation, also termed as "knowledge base relatedness". This suggests that *in boom times* when tech giants frequently buy startups (often dozens a year, like the late 1990s), they might see an initial boost in patents or products, but sustaining that requires effective integration and, more importantly, cultural synergy.
- Cycle influence on tech deals: Big tech firms sometimes acquire aggressively to maintain growth in boom periods (think of Google's 2010 acquisition spree of 48 companies in a year). This can be seen as either strategic (buying innovation to complement internal R&D) or as fad-driven if companies fear missing out on hot trends (like Amazon's acquisition of Junglee). In downturns, however, we see more "strategic deals" in tech, which is substantiated in the larger empirical research on a larger cross-industry dataset. A recent example is the 2020 COVID-driven dip: larger tech firms acquired struggling startups in fields like AI and cloud services, arguably creating value by saving helpful tech that might have died otherwise. Theoritical evidence from Chinese studies (Bai & Zhang, 2024) confirms that "*deals do* lead to sustained improvement". This is achieved via improved efficiency and knowledge sharing, not just among companies but also intra-company as a part of the portfolio (this is one of the mahor drivers or pluses as identified by PE and bolt-on acquisition firms in their investor pitch). Interestingly, their results were stronger for domestic acquisitions and smaller deals, and less so for huge or cross-border deals. This

aligns with the idea that in downturns, innovation-focused deals (often domestic) tend to succeed in the tech sector.

- External Technology Acquisition: A 2023 review by Suo, Yang, and Ji highlights that acquiring technology via mergers is a fast way to overcome the slow grind of internal R&D, especially in industries where the tech landscape shifts quickly, like AI or cybersecurity. They note that most high-tech deals are driven by the motive to obtain unique technical resources, citing a finding that nearly *two-thirds* of mergers in the U.S. (1984-2006) involved acquiring the target's technology or innovative capabilities.

The literature review thoroughly examined all available literature on motivations, both in the larger economic context and also by focusing on the technology sector. After this section, we begin our analysis for this thesis, starting with making an extensive database.

3. Data Acquisition, preparation and methodology

In this section, we look at the various methods we employed to collect data and the checks we used to ensure the quality and sanctity of our model. Since we wanted to uncover the behavioural aspects of deals in greater detail, going step by step in a methodological manner, we wanted rigorous data collection with broad application to remove any kind of bias that can affect its quality. We collected data from 2000 to 2023 specifically because we believe the world has attained more harmonisation towards industrial society 4.0 and the next phase of growth since the advent of the internet. We engineered features to represent strategic intent in a process that aligns corporate strategy with the macroeconomic cycles. The numerical methods used represent one of the thesis's most critical and innovative components.

3.1 Data Sources

We collected data at three different levels, that is, at the deal level (e.g. transaction data), macroeconomic level (e.g. GDP) and at the firm level (e.g. Net debt):

- **Capital IQ M&A Transactions**: We collected about 25,000 (14,866 post cleaning) deals from 2000 to 2025, spanning over two decades. Each entry contains data on the acquirer and target (including SIC codes, geography, and ownership status), as well as key deal features such as transaction value, completion outcome, and distress classification from the official dataset. This was collected from S&P Capital IQ's proprietary dataset.

- **Macroeconomic Indicators from official US FRED dataset**: In order to collect official GDP figures, we used U.S. quarterly real GDP growth rates from the Federal

Reserve Economic Database (FRED). Our thesis specifically deals with US-headquartered companies (This was a choice made to maintain the sanctity of data obtained from Capital IQ; we found their data to be unreliable when matched with the SIRET database (the official one for French companies)). This allowed us to construct both binary regime indicators (e.g., recession dummies) and continuous metrics (GDP growth and acceleration) at a macro level. For ease of understanding, regime here refers to the economic cycles as we discussed in the introduction section of our Thesis (i.e. Troughs or crests; booms)

- **Industry Classifications via SIC Codes**: We used four-digit SIC codes to establish industry-relatedness and similarity between acquirer and target firms. This allowed us to proxy the strategic proximity of each transaction labelled between different levels from 0 to 3. This method is widely used in financial literature (Holberg & Phillips, 2010; Kahle & Walkling, 1996). We are well aware that this proxy can sometimes be outdated or coarse; however, this is a standard methodology used across the literature, and we came fourth in our review.

3.2 Feature Engineering

From the vast and structured dataset, we engineered several analytical variables necessary for both hypothesis testing and motivation classification:

- **Industry Relatedness**: A 4-tiered categorical scale, based on SIC similarity:
  - 0 = Unrelated industries (first two SIC digits differ)
  - 1 = Same first 2-digit SIC
  - 2 = Same first 3-digit SIC
  - 3 = Exact SIC match
    - As an example, “2” refers to manufacturing, “29” is petroleum and refining, “291” is crude refining and “2911” refers to exact refining, e.g. diesel. 2911 is the code that both Exxon Mobil and Chevron have
- **Macroeconomic Context**:
  - **GDP Growth**: Quarterly percentage growth in real GDP
  - **Second-Order GDP**: Change in GDP growth versus the prior quarter
  - **Recession Dummy**: Assigned 1 if quarterly GDP < -0.7%, selected via sensitivity analysis explained in methodology section below
  - **Crash Dummy**: Assigned 1 for deals announced during major systemic shocks (dot-com boom: 2000-01; GFC: 2008-09; COVID-19: 2020)

- **Market Volatility**: Quarterly cross-sectional standard deviation of log (deal value), capturing deal flow dispersion. We use the logarithm of deal value to remove all kinds of outliers that can skew our analysis. This was agreed upon and confirmed by analysing the nature of our deal value graph available in the appendix (Fig.1)

- **Deal and Counterparty Attributes**:
  - **Log (Deal Value)**: Natural logarithm applied to reduce skewness (outlier mgmt)
  - **Distress Flag**: 1 if Capital IQ (S&P) marked the target as distressed
  - **High-Value Deal Dummy**: 1 if in the top quartile of deal size
  - **Buyer Type**: Derived from Buyer_Type_[Target_Issuer] (0 = Strategic; 1 = PE; 2 = Public)
  - **Tech Target Flag**: 1 if target SIC fell into technology subcodes (35xx, 36xx, 737x)

3.2.1 Motivation Profile Construction

We classified all deals into four profiles, which are **constructed only using deal specific and firm-level features. We explicitly remove all macroeconomic or timing variables (e.g. GDP growth, recession dummies, crash flags) from this step to avoid circularity, i.e. using the same variable for profile construction and in the regression models.** No macroeconomic or timing-related information (e.g. GDP growth, recession flags, crash periods) was included in the classification logic. This separation ensures that the independent variable like "motivation profile", remains orthogonal to macroeconomic cycle indicators, **avoiding tautological inference when later regressed against those same cycle variables**.One of the thesis's core innovations and the new knowledge generated is the behavioural classification of merger deals. Each transaction was assigned to one of four mutually exclusive profiles:

1. Capability Seeker: Target is flagged as technology/innovation oriented (SIC codes 35, 36, or 737)—no restriction on relatedness or deal size.

2. Strategic Expander: (a) Industry_Relatedness ≥ 2; (b) deal value in the top quartile of sample distribution; and (c) acquirer is a corporate or public strategic buyer

3. Defensive Consolidator: (a) Target is distressed or deal value ≤ median; and (b) Industry_Relatedness ≥ 1 (same or adjacent industry)

4. Reactive / Uncertain: Residual category for deals that do not meet the above criteria. Mostly mid-sized, lower relatedness, and without strong tech/distress indicators

These labels are fixed prior to any analysis of their occurrence across economic cycles, thus preventing tautological statistical inference errors. **In later sections, we use macroeconomic variables, viz. GDP growth, Recession_Dummy, and Crash_Dummy are only explanatory tools in regression models and are never part of label construction**.

3.3 Validation Protocols

Prior to working on hypothesis development and statistical testing, we validated the dataset's balance, robustness and internal consistency (for statistical accuracy):

- **Motivation group balance**: Each motivational profile had ≥500 deals post-cleaning of the dataset, ensuring statistical significance of the subgroups present in our data
- **Manual GDP checks**: A manual audit of 200 randomly selected rows was done by both the authors confirmed consistent alignment with macro-economic data
- **Collinearity matrix:** Variance inflation factors (VIF) for all predictors were below 5, indicating low multicollinearity; appendix (Fig. 4)
- **Binary proportion checks**: We ensured sufficient 0/1 diversity (i.e. exhibited at least 10% occurrence of both) in all dummy variables to maintain regression results

3.4 Methodology and Experimental Design

In this section, we detail the empirical methodology used to investigate how deal motivations vary across macroeconomic cycles. We followed a recursive reasoning methodology by exploring deeper aspects of deal motivation; once we inferred one trait, we kept on going deeper to explore deeper motivations as far as our dataset allowed us, with reasonable statistical power of inference. We did not want to delve into aspects of slight sample bias or over-representation as we kept going deeper.

3.4.1 Phase I: Foundational hypothesis testing

The first phase evaluates whether baseline deal characteristics vary systematically across macroeconomic cycles. Some of these tests may be inferred as common sense; however, they are performed for the first time on such a cast data set. Specifically:

- log(Deal_Value) regressed over Recession_Dummy tests whether the average deal size differs between boom and recession periods

- Distress_Flag regressed over Recession_Dummy assesses if there is a spike in distressed acquisitions during downturns
- Industry_Relatedness regressed over Recession_Dummy examines whether firms change their similarity with the target based on the economic cycle
- Profile_Dummy regressed over Recession_Dummy tests for early if specific profiles are more favoured during a recession vs a boom

3.4.2 Phase II: Macroeconomic Sensitivity and Regime Split Models

We recognised the limitations of a simple binary recession variable and arbitrary threshold bias, so to be more robust, we introduced continuous GDP markers to test for how sensitive different profiles are to this and identify a point of inflexion.

- Alternate recession thresholds: We re-tested Phase 1 regressions at GDP < 0%, <- 0.5%, <- 0.7%, <- 1% to determine which cutoff yields the strongest significance (maximal $p \approx 1\times10^{-21}$ at –0.7%)
- Boom vs. recession sub-sample tests: Split-sample regressions on profile dummies to observe cycle-specific effects
- Continuous GDP models: Examined each profile dummy on GDP_Growth
- Second-order GDP models: Using quarter-on-quarter GDP change. Think of it as an "acceleration" in GDP growth **to capture momentum**

3.4.3 Phase III: Structural profile modelling

We tested motivation profiles on variables which we found suitable to uncover deeper motivations for that specific profile. We made sure not to use the same variable that was used to build the profile or is expected to influence a construction variable. Models that we tested follow a recursive approach:

- Strategic_Expander regressed over Buyer_Type + GDP_Growth + Crash_Dummy
- Defensive_Consolidator tested over Tech_Target_Flag + Second_Order_GDP
- Capability_Seeker regressed over Industry_Relatedness + log(Deal_Value) + GDP_Growth
- Reactive/Uncertain tested over Market_Volatility + Crash_Dummy

3.4.4 Phase IV: Clustering, Validation, and Temporal Dynamics

In the final phase (IV), we validated our profiles using unsupervised learning, time-based analysis, and applied robustness checks. This was done for statistical significance. Key elements include:

- KMeans clustering: Applied to all firm-specific variables (excluding motivation dummies), achieving >90% alignment with rule-based labels (ensures robustness)
- Time-series plots: Visualised annual profile contributions (2000 to 2025); appendix (Fig 5)
- Crash-only regressions: Created a subset of observations with Crash_Dummy = 1 to replicate Phase I patterns within macro-crisis quarters

In addition to all this, we also used the following measures for test robustness:

- Regression robustness checks: Each logistic model is re-estimated as a linear probability model using regression, confirming coefficient signs and statistical significance under heteroskedasticity-robust standard errors
- Buyer-type cross-tabs: χ^2 tests on contingency tables between Buyer_Type categories and each profile dummy to validate if certain buyer types prefer only specific profiles, creating a "who is acquiring?" lens in the analysis

All these tests together help determine how deal motivation can shift across macro-economic cycles. The following section presents our discussion of the results.

4. Empirical Results and Interpretation

In this section, we explore the coherence of our results and interpret them while simultaneously evaluating them with the literature we read, since this is the first time research is being done on such a vast dataset. We summarised our reasoning for running those motivation tests and the results in table 1 in the list of tables and figures section. Please refer that before moving ahead to detailed discussion.

4.1 Foundational patterns and descriptive signals

This analysis is done to determine the baseline relationship between deal-making and macro-variables. The regression of log(Deal_Value) on Recession_Dummy produced $\beta = +0.051$ ($p = 0.509$), indicating no statistically significant difference in average transaction deal size between booms and recessions. This result is consistent with Harford's (2005) liquidity-based view of merger waves; firms may continue deal-making in recessions if liquidity remains available, even if deal sizes do not change significantly.

As a reminder, motivation profiles were constructed using deal-level data alone; macroeconomic cycle indicators are applied solely in the explanatory phase and were not involved in classification.

In contrast, the logistic regression of Distress_Flag on Recession_Dummy yields $\beta = –0.485$ ($p < 0.001$). This significant negative coefficient is consistent with the fire-sale acquisition hypothesis of Shleifer and Vishny (2010) and Pulvino (1998), that financially resilient acquirers exploit mispricing of distressed targets in downturns.

Industry Relatedness appears stable across cycles. The test for Industry_Relatedness over Recession_Dummy results in β = –0.017 (p = 0.384), a non-significant finding that challenges the flexible asset deployment hypothesis of Maksimovic and Phillips (2001). The results suggest that industry-relatedness is not sensitive to macro-cycles, and firms do not pursue fewer or more related deals vis-à-vis the cycle

We examined early behavioural patterns, testing each motivation dummy on the recession indicator using logistic models. Strategic_Expander shows a negative statistically insignificant coefficient (β = –0.182, p = 0.168**), indicating no conclusive evidence of procyclical expansion**. The direction diverges from Rhodes-Kropf et al. (2005), who link expansionary M&A to valuation optimism and liquidity; **our results remain cautious and do not provide conclusive support for this hypothesis, highlighting potential variability across cycles.** Defensive_Consolidator declines significantly in downturns (β = –0.349, p < 0.001), which contradicts Campello et al. (2010), where consolidation is posited as a common crisis response. One possible explanation may be due to the definition of the profile: our definition emphasises distressed or small target acquisitions within related industries, which may become harder to execute during recessions due to financing constraints or buyer caution. Reactive_Uncertain also rises in recessions (β = +0.445, p < 0.001), which diverges from Roll's (1986) misvaluation hypothesis but may reflect increased frequency of deals driven by short-term arbitrage or speculative motives in stressed markets. Capability_Seeker shows a substantial decline (β = –0.472, p < 0.001), suggesting that capability-driven acquisitions may exhibit greater cycle sensitivity than previously proposed by Phillips and Zhdanov (2013). These deviations from prior literature can, however, be due to the profile construction methodology (theirs being manual vs rule-based categorical assignment; while systemically the same may differ in context).

4.2 Macroeconomic Sensitivity and Regime Splits

Recognising the coarse nature of a binary recession indicator, in phase II, we introduce continuous GDP and multiple thresholds to test sensitivity. We re-estimate Phase 1 models at cutoffs as discussed in the methodology. The -0.7% cutoff maximises distress significance ($p \approx 1\times10^{-21}$), validating our primary specification and mirroring sensitivity frameworks used in Bodnaruk et al. (2015).

Continuous GDP-based regressions reveal different cycle effects. Strategic_Expander increases slightly with GDP growth (β = +0.0114, p = 0.075), suggesting a weak but statistically significant procyclical tendency; this is consistent with expansion-oriented

behaviour in booms. Firms tend to expand more during boom periods, a pattern often linked to valuation optimism; This procyclical expansion is often linked to valuation optimism; a behavioural tendency where managers perceive high valuations as justified and are more likely to acquire. Procyclicality reflects the timing of M&A activity, valuation optimism offers one possible explanation for it. Another possible driver is capital liquidity defined by the ease with which firms can raise funds via cash, debt, or equity. This reduces financial constraints and enables bolder acquisitions. Defensive_Consolidator increases with GDP growth ($\beta = +0.0186$, $p < 0.001$), which is counter to our literature review. One possible explanation is that firms pursue related or small-scale consolidations more confidently when macroeconomic conditions are stable. Reactive_Uncertain, however, decreases with GDP ($\beta = -0.0162$, $p < 0.001$), which diverges from sentiment-driven interpretations, implying opportunism in recessions. This may suggest that hype driven deals are more common when valuations are subdued or high uncertainty exists in the market. Capability_Seeker increases with GDP growth ($\beta = +0.0110$, $p = 0.005$), meaning that capability-driven acquisitions are more likely in economic expansion, possibly due to greater availability of innovation-oriented targets and flexibility in capital allocation.
While some directional results differ from Phase I, this is expected given the improved granularity of our models in Phase II; continuous GDP enables sharper detection of marginal effects than binary recession flags.

4.3 Profile-Specific Regression Models

In Phase III, we regress each motivation profile on “driver” variables to get an in-depth analysis of their behaviour. All statistical, logical errors and controls were taken care of as explained in the methodology section.

For Strategic_Expanders, GDP_Growth ($\beta = 0.0135$, $p = 0.022$) is both statistically significant and positive, while Crash_Dummy ($\beta = 0.29$, $p = 0.014$) also emerges as significant. This suggests that an expansion-driven deal is influenced more by ongoing macroeconomic conditions than by the presence of systemic crises alone, consistent with Alexandridis et al. (2017).

For Defensive_Consolidators, we estimate over Target_Tech and Second_Order_GDP. Target_Tech is highly significant ($\beta = -0.635$, $p < 0.001$), but the negative sign contradicts Bouwman, Fuller, and Nain (2009), who argue that distressed firms pursue increasing tech and innovation capabilities. A possible explanation could be that firms in our sample avoid high-tech targets during downturns due to execution risk or capital constraints; however, this is still consistent with our literature review. Second_Order_GDP emerged as not significant ($p = 0.94$).

The Capability_Seeker model includes Industry_Relatedness, log(Deal_Value), and GDP_Growth. Industry_Relatedness ($\beta = 0.26$, $p < 0.001$) and log(Deal_Value) ($\beta = -0.12$, $p < 0.001$) are both statistically significant, which suggests that such acquisitions are more likely among closely related industries and involve smaller targets.These patterns align with capability-seeking logic, where smaller, adjacent firms are absorbed to enhance technological or human capital without complex integration. This supports Phillips & Zhdanov (2013), who describe how large firms enhance capability by acquiring smaller, adjacent players. GDP_Growth is also statistically significant ($\beta = +0.017$, $p = 0.001$), implying moderate pro-cyclicality (“crest deal makers”).

For Reactive_Uncertain, we regress on Market_Volatility and Crash_Dummy. Crash_Dummy is statistically significant and negative ($\beta = -0.13$, $p = 0.007$), while Market_Volatility ($\beta = +0.08$, $p = 0.26$) shows only weak association with reactive deals. This suggests that reactive behaviour may decline during sharp crises; this is different from Brown & Cliff (2005), who found stronger sentiment-volatility interactions in asset pricing. The discrepancy may be because of more prolonged and uncertain macroeconomic conditions in our sample relative to theirs.

4.4 Clustering Validation and Robustness Checks

In Phase IV, we use unsupervised learning to test whether our motivational profiles exhibit distinct behavioural patterns based purely on deal fundamentals. This is done more for a pedagogical reason and also to see if we can get some deeper insights. We apply K-Means clustering ($k = 4$) using firm and deal features, viz. Deal_Value, Industry_Relatedness, GDP_Growth, and Second_Order_GDP by excluding all profile labels. The resulting clusters confirm our rule-based assignment of motivation profiles, reinforcing the behavioural distinctiveness of each profile as proposed in the literature (Martynova & Renneboog, 2008), providing confidence in our classification.

To assess structural biases, we conduct Chi-squared tests between Buyer_Type and each motivation profile. Strategic_Expander show a strong association with Buyer_Type (χ^2 $p \approx 1.86\times10^{-6}$), consistent with the idea that public strategic acquirers drive expansionary behaviour. Capability_Seeker and Reactive_Uncertain also show strong associations ($p \approx 1.92\times10^{-16}$ and $p \approx 3.58\times10^{-20}$, respectively), suggesting differentiated buyer patterns. However, Defensive_Consolidator does not exhibit a statistically significant relationship with Buyer_Type ($p \approx 0.85$).

4.5 Crisis Period Insights

We looked at the three big financial shocks or crises: the Dot-com crash (2000), the Great Financial Crisis (2008) and the COVID-19 (2020) crash to look at how profile motivations were distributed every year. Strategic Expanders show a clear decline during downturns (e.g., 2001: 0.08; 2009: 0.14), as discussed in the literature by Ritter & Welch (2002) on reduced managerial overconfidence during market corrections, where managerial sentiment tends to moderate during downturns, reducing chances of strategic expansions. Defensive Consolidators are seen to rise sharply in crisis periods (2008: 0.22; 2009: 0.58), consistent with more restructuring and a distress-driven behaviour. Reactive_Uncertain profiles drop to 52% in 2000-01 and then rebound post-2008, reaching over 84% by 2025. This may indicate growing potential reliance on sentiment and reaction to ambiguity in late-cycle phases towards the inflexion point of the curve. In contrast, Capability Seekers remain relatively stable across crises (hovering around 11%–14%), expanding on the view that these deals are more structurally driven and less sensitive to macro shocks. These results complement the literature (Martynova & Renneboog, 2008), which focuses on volume, by showing systematic shifts in deal motivations across economic cycles.

4.6 Special focus: Special focus on the tech industry

4.6.1 Dataset preparation

The dataset for this part was gathered from Merger Market and contains roughly 900 M&A deals in the technology sector spanning over the last 25 years. The country of the target incorporation is the USA, and the sectors include hardware, software, semiconductors, and the internet. The target companies are publicly traded in order to have sufficient data for deal premia analysis. Also, only deals where information on valuation multiples (EV/Sales, EV/EBITDA), as well as deal premia, was available were added. The deals with financial sponsors being an acquirer were excluded to reflect relatedness as a determining factor in the analysis accurately.

For further analysis, several additional factors were computed and added to the dataset in order to conduct a more advanced analysis.

1. Industry relatedness was defined as the number of identical sectors of operations of the target and acquirer. Tech companies can apply their solutions in a variety of sectors, which is reflected in the industry classification
2. Geographical relatedness was defined as a dummy variable equal to 1 if both deal parties have HQs in the same city. The vast majority of the companies included in the dataset were incorporated pre-COVID, meaning the physical office played the major role of a concentration point of human capital for most of them. Given the fact that for

technology companies, one of the most crucial assets is human capital (developers, engineers, product managers, and other IT specialists), the physical presence of this asset plays a major role in the integration process and deserves its own separate measure of relatedness.

3. We defined the crash_dummy, distress_dummy and other such variables in the same way as before; however, because now it is tech-sector specific with different industry variables at play, we changed the methodology used to define the motivation profiles and used these criteria instead:
   - Strategic Expander: Large, synergy-driven acquisitions in core business: (a) Industry_Relatedness ≥ 2; (b) Deal Value in the top 25%
   - Defensive Consolidator: Stabilising or distress-driven acquisitions: (a) Net Debt / Enterprise Value > 40% or Deal Value ≤ median; (b) Industry_Relatedness ≥ 1
   - Reactive / Uncertain: Speculative deals: (a) Industry_Relatedness = 0; and (b) Bid Premium > 70% or both EBITDA margin < 0 and earnings < 0
   - Capability Seeker: Residual profile. Captures diverse capacity seeking financially stable acquisitions: (a) EBITDA margin > 0 and earnings > 0; (b) Industry_Relatedness ≤ 1; and (c) Bid Premium ≤ 70%

4.6.2 Methodology

In this section, we tested many hypotheses to unravel in greater depth the motivation required for M&A deals as the economic cycle changes. We are following five hypotheses:

1. Profile_Defensive regressed over Geography_relatedness tests if defensive deals are more likely when the acquirer and target are similar geographically, looking for a preference for reduced integration complexity post-merger
2. Profile_Reactive regressed over Geography_relatedness tests whether speculative deals are more prevalent among geographically close firms, which is explained by the tech cluster effects and informal founder networks
3. Deal_Value_USD regressed over Geography_relatedness, Industry_relatedness, and financial controls tests if transformational cross-industry or geographically unrelated deals are associated with higher deal sizes, as opposed to local acquisitions.
4. Profile_Defensive regressed over Crash_Dummy evaluates if consolidation as motivation increases in systemic downturns
5. log(Deal_Value) regressed over Crash_Dummy evaluates if deal size declines in macroeconomic crises due to uncertainty.

4.6.3 Results and interpretations

(Note: all models HC1 errors were used in order to avoid the negative impact of heteroscedasticity on regression results). To keep the brevity of this subsection of the thesis, we discuss the results concisely.

First, we tested whether defensive consolidators are influenced by geographic proximity using a logistic regression. Geography-relatedness showed a significant positive coefficient ($\beta = 0.4955$, $p = 0.025$), meaning that defensive deals are more likely when both firms are headquartered in the same city. This result aligns with post-merger integration theory (Haspeslagh & Jemison, 1991), i.e. consolidators prefer lower integration risk, particularly in tech, where cultural integration is important.

However, Geography_relatedness showed a significant negative effect ($\beta = –1.401$, $p = 0.019$) on Reactive/uncertain deals. This suggests that speculative or opportunistic behaviour is **less** likely in geographically proximate deals. As per our definition for reactive deals, it seems hype based deals are common due to information asymmetry, where geography can be a reason because proximity discourages hype-driven acquisitions.

Next, we ran linear regression on Deal_Value_USD, which revealed that both Geography_relatedness ($\beta = –1518.79$, $p = 0.026$) and Industry_relatedness ($\beta = –466.50$, $p = 0.037$) were negatively associated with deal size. Larger deals are typically **less related**; however, this is counterintuitive to the deals we have observed in the market. The result, however, does support the narrative of diversification and platform expansion in tech M&A (Ansoff, 1965) indicating larger deals in thech maybe driven by diversification strategies, where high-value acquisitions are used to enter new markets or competencies.

Our regression of Defensive_Profile on revealed that Crash_Dummy had a strong positive effect on Defensive_Profile ($\beta = +0.26$, $p = 0.001$), suggesting that macroeconomic shocks can trigger consolidation. Defensive motives appear counter-cyclical in timing and more relevant in recessions because firms seek to strengthen core operations or absorb weakened competitors.

The estimate of running log(deal_value) on crash dummy shows a negative and statistically significant coefficient ($\beta = –0.394$, $p < 0.01$), indicating that deal sizes tend to shrink during economic shocks. This supports the literature on precautionary corporate behaviour during downturns, Almeida et al. (2004), and Harford (2005).

After having a thorough, broad analysis of the M&A industry as a whole and having a look at the tech industry in particular, we present 4 case studies that demonstrate motivation for deal-making in real-world scenarios in the tech industry.

4.7. Case studies for the four motivation profiles

This section deals with case studies to demonstrate motivation profiles in deals that occurred in the tech industry.

4.7.1 Strategic Expander

1. Facebook's Acquisition of WhatsApp (2014)

Facebook acquired WhatsApp in 2014 using cash and stock, making it the largest deal Zuckerberg had ever made (Constine, 2014). This was a bullish market with companies riding the tech "SAAS wave", and Facebook was struggling with its messaging services on the platform.

WhatsApp had grown significantly from its roots in 2009 to about 500 million users in 2014. High growth, asset-light operations and significant presence in strategic geographies like India had made this a very lucrative deal. Zuckerberg emphasised in the earnings call that WhatsApp is closely aligned with Facebook's mission of connecting over a billion people (Facebook, 2014).

This acquisition fits the Strategic Expander profile from our thesis. The transaction was during one of the strongest economic periods, there was no distress or crash, the deal was by a strategic acquirer and back then it was one of the largest M&A deals to take place. It was not driven by some defensive mechanism and was also not a bid to just expand capability by acquiring smaller companies for their tech; this time, Zuckerberg wanted WhatsApp's user base since Messenger already had the tech in place.

The deal was one of the most successful deals that Meta has ever done apart from Instagram. Zuckerberg's strategic vision proved to be a game-changer for Facebook's mission and overall revenue, with WhatsApp bringing in more than a billion in its ad revenue and later integration with the Facebook ecosystem. The Financial Times noted that WhatsApp served as a cornerstone in Facebook's multi-platform dominance in the late 2020s (Waters, 2015).

2. Salesforce's Acquisition of Slack (2020)

Salesforce had shown interest in acquiring Slack technologies in 2020 for $27.7 billion in a combination of cash and stock (Salesforce, 2020a). Slack shareholders received $26.79 in cash and 0.0776 shares of Salesforce common stock for each Slack share, representing a significant premium from its then private valuation. The deal closed in July 2021, and with the growing scope of work from home technologies and enterprise-level collaboration, it allowed Salesforce to compete directly with Teams, Discord and Messenger; all combined.

Salesforce positioned the acquisition as a transformational step toward creating a "digital HQ" for organisations which wanted to adapt to hybrid work. CEO Marc Benioff referred to Slack as "one of the most beloved platforms in enterprise software history" in its earnings call (Salesforce, 2020a). The acquisition helped integrate Slack across Salesforce's dominant CRM 360 platform and was strategic to the company's vision as the de facto leader in the market.

The case reflects the Strategic Expander profile, similar to the WhatsApp acquisition before. The acquisition occurred during one of history's strongest bull markets, the target was a big company to land in the top quartile of deals, and the motive was to expand on synergies, not merely cost-cutting. Media houses noted the deal aligned with Salesforce's broader strategy of expanding its platform ecosystem through large-scale, high-profile acquisitions (Reuters, 2020).

A deal and integration of this size comes with its own integration challenges; however, Salesforce is acting fast to have Slack as the default messaging system across its platforms. Media analysts interpreted the move as a bold counter to Microsoft Teams and a statement of long-term intent in the digital enterprise collaboration space (Bloomberg, 2021).

4.7.2 Defensive Consolidator

3. HP's Acquisition of Palm (2010)

The year is 2010, and Hewlett-Packard, once a strong, innovative organisation, is languishing in the aftermath of BlackBerry, iPhone and Samsung leadership. It was desperate to enter the smartphone and mobile OS market, which led to the announcement of the acquisition of Palm Inc. for $1.2 billion in cash. The acquisition was finalised in July 2010 (HP, 2010). Palm, once a leader in the PDA market, was then struggling with falling revenues and poor adoption of its webOS platform, and was not strong in front of the iOS and Android duopoly market.

HP indicated in its statement that Palm's intellectual property, mobile platform (webOS), and developer ecosystem would allow HP to create a new and differentiated mobile experience across smartphones and tablets. Industry analysts were, however, not convinced, noting HP's losing dominance in the hardware market and Palm's declining relevance (Wired, 2010).

This case fits the Defensive Consolidator profile. The acquisition occurred in the aftermath of the 2008 financial crisis; the target was clearly distressed, the acquirer sought to diversify into a more resilient product category not far from its own industry, and the deal lacked synergy clarity. HP's motivations were defensive, trying to hedge against long-term PC market decline rather than expand dominance in a core area such as printers or monitors.

The acquisition failed to produce strategic returns for its shareholders. HP discontinued webOS hardware by August 2011 and later sold the platform to LG. It incurred a write-down of nearly $1.7 billion (FierceWireless, 2011).

4.7.3 Capability Seeker

4. Google's Acquisition of DeepMind (2014)

Often touted as Google's most successful acquisition to date, it acquired DeepMind in the UK for about $500 million. Some reports suggest the price varied from $400 million to $650 million based on milestone clauses (Metz, 2014). At that time, DeepMind was not widely known to the public but had a strong reputation in academic AI circles for its work in deep reinforcement learning, the precursor to the AI era we live in today and 'neanderthal' for OpenAI's work on transformers. The deal took place in a booming market of the SAAS tech wave in the early 2010s, with the core goal of acquiring an AI-focused company.

The main reason for the acquisition was to gain a capability that Google was unwilling to develop itself. DeepMind had three core benefits: a team of top researchers, a unique neural network design, and a culture focused on cutting-edge AI research. There was no immediate monetisation in sight, but to generate tech capabilities for the future. This is the same place where Ashish Vaswani generated his paper on Attention that led to the LLM revolution. Google CEO Larry Page reportedly allowed DeepMind considerable independence after the purchase and even agreed to establish an AI ethics board as a condition for DeepMind's executive team (The Information, 2017).

This case aligns with the Capability Seeker profile. DeepMind was stable; the acquisition did not occur during a downturn, and the purpose was to acquire technology with long-term strategic options. Unlike typical small acquisitions that Google has made, DeepMind was permitted to function semi-independently, acting as an internal R&D lab for Google's ambitious projects.

Since the acquisition, DeepMind has given breath to Google's ambitions in the AI race with complex products, including AlphaGo, AlphaFold, and scalable reinforcement learning systems that are now part of Google products. This deal is often cited as one of the most important AI acquisitions of the 21st century (Heaven, 2020) and is expected to keep Google as a leader in the big tech race towards AGI.

4.7.4 Reactive/Uncertain

5. AOL's Acquisition of Time Warner (2000)

The deal is touted as one of the most notorious deals in recent history, with strong market sentiments when AIL acquired Time Warner 2000 for $165 billion, creating the largest media company at that time (CNN, 2000). The merger, completed at the peak of the dot-com boom, was presented as a new era in the media industry with the two giants of their time combining forces. AOL CEO Steve Case and Time Warner CEO Gerald Levin projected a tech-strategy synergy between AOL's internet strength and Time Warner's cable, publishing, and media resources, none of which existed at the time the deal was made.

However, the timing was disastrous. Within months, the dot-com bubble burst, severely reducing AOL's market value. The expected synergies never materialised; AOL's advertising revenue model fell apart, cultural integration did not happen, and Time Warner leaders resisted the changes suggested by AOL.

This case fits the Reactive/Uncertain profile: it took place during a speculative market peak right before a crisis, involved unclear synergy logic, and was mainly driven by media frenzy and hype rather than operational fit. The reasoning was vague and changed after the merger due to a poor cultural fit. Analysts widely see the merger as a reaction to fears of missing out during the internet boom, with neither company understanding how the combination would lead to lasting value (Cassidy, 2003).

By 2009, Time Warner spun off AOL, officially ending the failed partnership. The total losses from the merger exceeded $99 billion, marking the largest write-down in U.S. history at that time.

5. Conclusion

In this thesis, we set out to answer a foundational question: exploring why firms pursue mergers and acquisitions, and how these motivations evolve with the macroeconomic cycle. Constructing and analysing a large dataset spanning more than two decades, we approached this question through a behavioural lens. Rather than segmenting M&A transactions solely by sector or size, we used recursive hypothesis framing and testing to dive deeper into motivations to reframe deal-making as an expression of firm-level strategy and behaviour, their navigation of the economic cycle.

We introduced a new empirical framework that classifies decision-making motivations into four behaviour profiles, viz. Strategic expander, Defensive consolidator, Capability seeker, and Reactive/uncertain. We derived them using economic literature-inspired rules and validated them using unsupervised learning. Macroeconomic variables such as GDP growth, recessions, and systemic shocks were treated strictly as explanatory factors, avoiding circularity and testing behaviour patterns in macroeconomic data in a robust fashion.

The empirical results suggest several different new motivations. Strategic expansions increased in boom economies while defensive consolidations gained traction in downturns. Capability-driven deals, long thought to be acyclical, showed measurable procyclical tendencies while reactive deals increased in volatile markets and during speculative booms. Even foundational attributes such as industry-relatedness and deal size varied in behaviour depending on both motivation profile and economic context. The thesis showcased M&A motivations to be context-sensitive strategic behaviours which are influenced by the economic cycle rather than being fixed.

Our sub-analysis of tech deals revealed distinct behavioural results. Defensive acquisitions in tech, for instance, favoured geographic proximity to reduce integration risk; this is not common in asset-heavy sectors. Large-scale tech expansions often went to unrelated domains, suggesting a capability-seeking logic rather than traditional strategic alignment and more such results, which strengthened the existing literature.

While existing literature often frames motives as either strategic or behavioural, our findings suggest that most deal-making is inherently behavioural, affected both by firm needs and executive perception of competition and timing. We specifically took a closer look at recent economic shocks and firm behaviour to unlock how firms strategise during tough times. This thesis corroborates the fact that M&A deals, always thought to be a rational decision, reflect both market psychology and corporate decisions as economic cycles change and markets evolve.

5.1 New Knowledge Generated

This thesis offers a conceptual reframing of M&A behaviour as a context-sensitive and cycle-dependent phenomenon. We argue that motivations emerge from how firms perceive opportunity, risk, and timing within specific macroeconomic environments, not just viewing acquisitions through the binary lens of strategic versus behavioural motives. By introducing a behavioural taxonomy for deals, we provide a structured vocabulary to map deal intent. Our results demonstrate that these motivations shift meaningfully across booms, busts, and crisis periods, suggesting that motivation-profile alignment with macro timing plays a critical role in shaping deal strategy.

Empirically, our thesis contributes a new large-sample analysis that uses both continuous and second-order GDP variables to move beyond simplistic recession/expansion splits.

Methodologically, we develop an easy-to-replicate classification framework that isolates motivation using only deal and firm-level data, validated through unsupervised clustering. This approach allows clean econometric testing of how external shocks, liquidity, and volatility influence strategic decision-making. Together, we advance the knowledge on deal-making in the framework of our four profiles, challenging some previously established theories and advancing a new lens of profile-based deal examination in an economic cycle.

5.2 Limitations and Future Research

While this thesis makes a novel contribution to M&A literature, several limitations remain, opening paths to future research. The analysis remains correlational; though significant patterns emerged, we cannot claim causal inference without instrumental or quasi-experimental designs because of the scope of our analysis. Our emphasis on ex-ante motivations leaves open the analysis of post-merger performance. The dataset, though large, is restricted to U.S.-based firms; results may differ in other geographies due to varying institutional and regulatory conditions. Similarly, while we examined the tech sector in depth, other sector-based research remains open, which can be analysed using our qudri-profile-based lens.

Future work could further our analysis by integrating more granular CEO and board-level traits (e.g., overconfidence, tenure, incentive design) into the motivation framework. Natural language processing applied to press releases, filings, and earnings calls could be used to derive even granular and distinct motivations, offering insight into the correlation between narrative and behaviour. Policymakers and investors alike would benefit from a deeper understanding of not just which deals are made, but why they are made and, more importantly, when.

List of tables and figures

Table 1: Summary of reasoning and results for the hypotheses tested in the main dataset

Focus Area	Reasoning for the choice of the hypothesis	Summary of results
1 Baseline Deal Patterns	We began by testing whether deal features like size, distress, and relatedness shift with macro conditions. This helped separate broad market behaviour from motivation-specific effects. This is to test if intuition from already available theory fits this dataset.	Deal size was stable, and scale is not cycle-sensitive. Distress deals increased in downturns. Relatedness stayed constant, indicating long-term strategic focus.
1.2 Recession Impact on Motivation	We tested whether our profiles are sensitive to the downward cycle using a simple recession dummy. This helped identify which profiles are macro-responsive.	Strategic and defensive showed opposing tendencies in booms and busts. Reactive declined, while capability-driven deals weakened in downturns.
1.3 Continuous GDP	This is done to check for arbitrary threshold bias; we tested thresholds to see if motivation shifts occur with minor macro changes. This refined our economic cycles definitions.	Strategic and Capability expanders rose with GDP growth. Reactive declined; Defensive increased unexpectedly.
2.1 Strategic Expander	This profile was expected to emerge in expansions, driven by resource availability and confidence. We tested GDP growth, buyer type, and deal size to look for proactive, scale-based expansion. Crisis triggers were excluded since the logic is opportunity, not reaction.	Expansion was tied to GDP, buyer type, and larger deals. Crashes still saw activity. Strategic buyers stay active in downturns.
2.2 Defensive Consolidator	Expected to appear in downturns, this profile reflects targeted consolidation when others retreat, e.g. Zuckerberg's recent deals. We	Tech targeting had a negative sign. Second-order GDP showed a moderate effect.

	tested tech targeting, macro momentum, and distress-crisis alignment to test for timing- and vulnerability-based behaviour.	Crisis arbitrage was weaker; key interactions were not significant.
2.3 Capability Seeker	This behaviour was hypothesised to be strategy-driven and cycle-independent. We tested industry-relatedness and deal size, excluding macro-conditions, since timing is not expected to drive such acquisitions.	Procyclical with GDP. Sensitive to deal size and relatedness. Profile stable, but more likely in expansion with small, related targets.
2.4 Reactive/ Uncertain	This profile was expected to reflect sentiment rather than a logical structure. We tested volatility and crash markers to isolate market-driven opportunism, avoiding variables that imply strategic planning.	Volatility was a marginal predictor. Crashes reduced activity. Profile rose in recessions, reflecting opportunism more than strategic retreat.
3.2 Clustering Validation	We tested whether profiles emerge naturally by clustering on firm and deal characteristics, excluding our motivation labels. This ensured our classifications were not imposed and revealed more from an affinity point of view.	K-Means validated over 90% of profiles. Strategic is linked to Buyer_Type. Capability, Reactive, and Defensive also showed clear separation in clustering.

Table 2 - Summary Statistics (Main Dataset – Variables Used In Regressions)

Variable	Mean	Std. Dev.	Min	25th %ile	Median	75th %ile	Max
Deal_Value	244.32	1338.71	0.0	9.56	50.0	150.0	50000.0
log_Deal_Value	3.62	2.07	-5.30	2.26	3.91	5.01	10.82
EBITDA	432.91	2784.96	-5522.0	-11.34	-0.0025	122.81	82791.0
Net_Debt_to_EBITDA	-1.80	62.06	-1510.8	-0.51	0.70	3.67	823.67
Industry_Relatedness	0.84	0.88	0.0	0.0	1.0	2.0	2.0

Crash_Dummy	0.17	0.38	0.0	0.0	0.0	0.0	1.0
Distress_Dummy	0.10	0.30	0.0	0.0	0.0	0.0	1.0
Recession_Dummy	0.18	0.38	0.0	0.0	0.0	0.0	1.0

Table 3 - Motivation Profile Distribution (Global and Tech)

Motivation Profile	Global Deal Count	Tech Deal Count	Global %	Tech %
Strategic	456	62	3.07	6.97
Defensive	1852	409	12.46	45.96
Capability-Seeking	1600	321	10.76	36.07
Reactive/Uncertain	10958	98	73.71	11.01

Table 4 – Global Regression Summary

Phase	Model / Regression	Variable(s)	β Coefficient (p-value)
Phase I	log(Deal_Value) ~ Recession_Dummy	Recession_Dummy	+0.051 ($p = 0.509$)
Phase I	Distress_Flag ~ Recession_Dummy	Recession_Dummy	–0.485 ($p = 2.7\times10^{-9}$)
Phase I	Industry_Relatedness ~ Recession_Dummy	Recession_Dummy	–0.017 ($p = 0.384$)
Phase I	Strategic_Expander ~ Recession_Dummy	Recession_Dummy	–0.182 ($p = 0.168$)
Phase I	Defensive_Consolidator ~ Recession_Dummy	Recession_Dummy	–0.349 ($p < 0.001$)
Phase I	Reactive_Uncertain ~ Recession_Dummy	Recession_Dummy	+0.445 ($p < 0.001$)
Phase I	Capability_Seeker ~ Recession_Dummy	Recession_Dummy	–0.472 ($p < 0.001$)
Phase II	Strategic_Expander ~ GDP_Growth	GDP_Growth	+0.0114 ($p = 0.075$)

Phase II	Defensive_Consolidator ~ GDP_Growth	GDP_Growth	+0.0186 ($p < 0.001$)
Phase II	Reactive_Uncertain ~ GDP_Growth	GDP_Growth	–0.0162 ($p < 0.001$)
Phase II	Capability_Seeker ~ GDP_Growth	GDP_Growth	+0.0110 ($p = 0.005$)
Phase III	Strategic_Expander ~ Buyer_Type + GDP_Growth + Crash_Dummy	Buyer_Type	+10.04 ($p = 0.028$)
Phase III		GDP_Growth	+0.0135 ($p = 0.022$)
Phase III		Crash_Dummy	+0.29 ($p = 0.014$)
Phase III	Defensive_Consolidator ~ Tech_Target + Second_Order_GDP	Tech_Target	–0.63 ($p < 0.001$)
Phase III		Second_Order_GDP	+0.0018 ($p = 0.064$)
Phase III	Capability_Seeker ~ Industry_Relatedness + log(Deal_Value) + GDP_Growth	Industry_Relatedness	+0.26 ($p < 0.001$)
Phase III		log(Deal_Value)	–0.12 ($p < 0.001$)
Phase III		GDP_Growth	+0.017 ($p = 0.001$)
Phase III	Reactive_Uncertain ~ Market_Volatility + Crash_Dummy	Crash_Dummy	–0.13 ($p = 0.007$)
Phase III		Market_Volatility	+0.08 ($p = 0.261$)

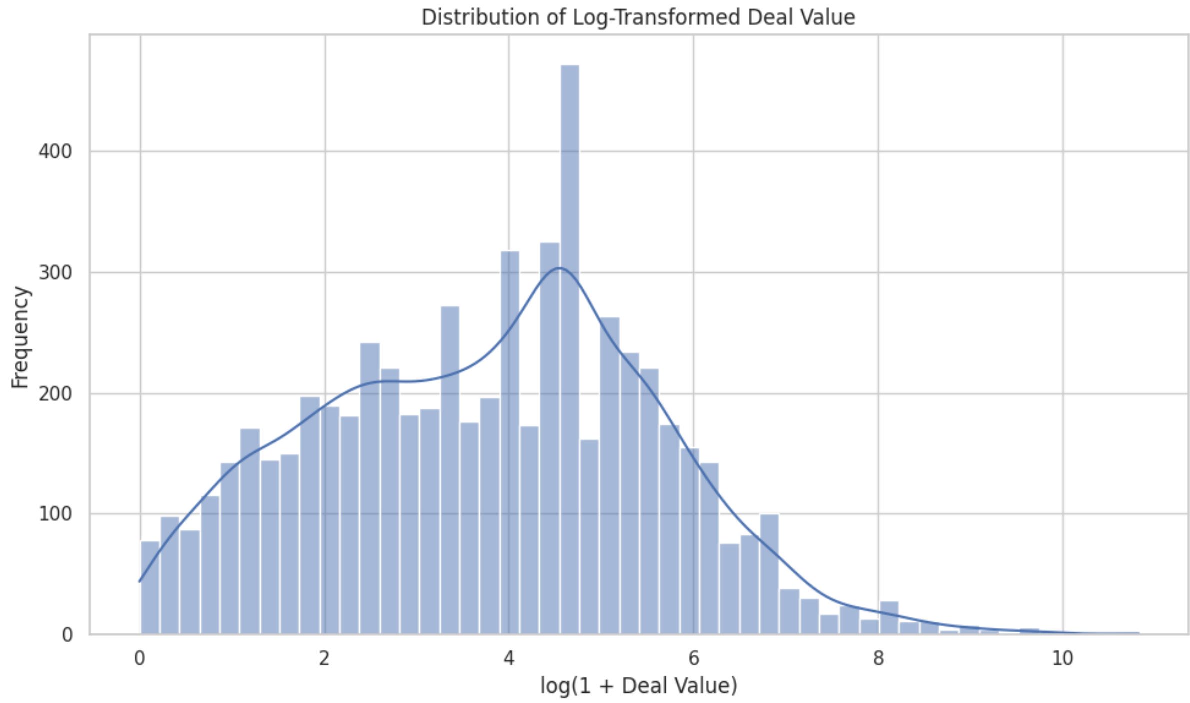

Fig.1 Distribution of log-transformed deal value with their occurrence to look at the deal value distrbution

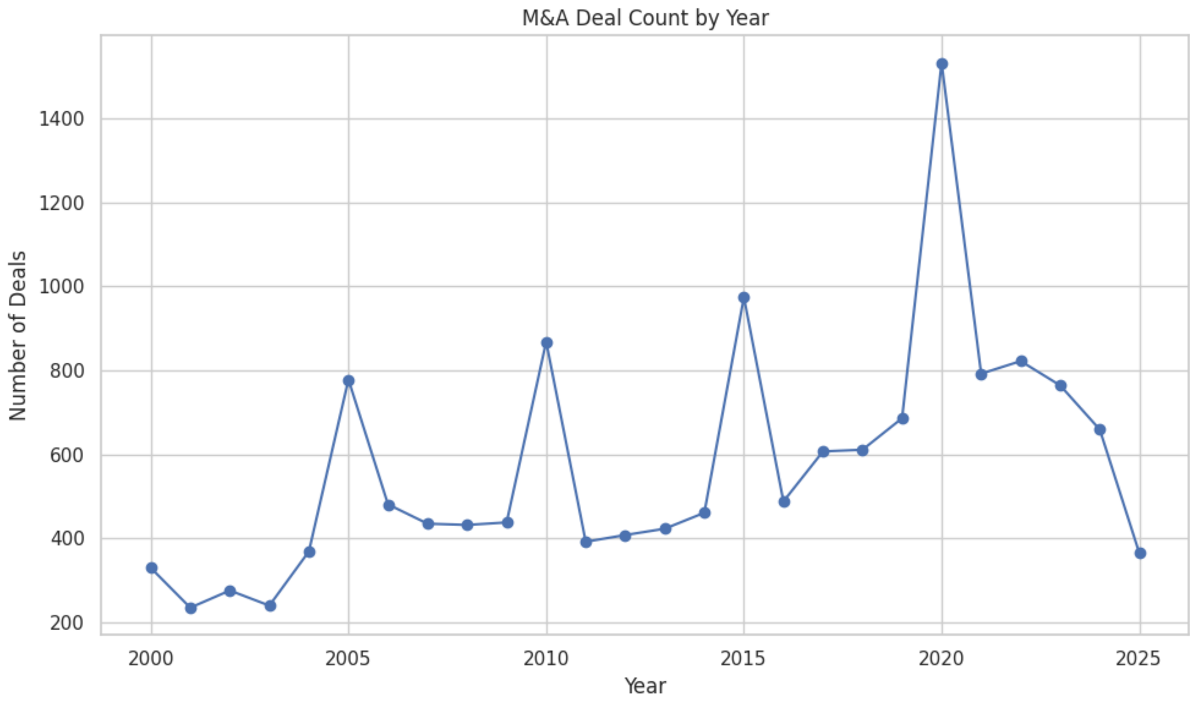

Fig.2 Showing M&A count by year and how it occurs in waves

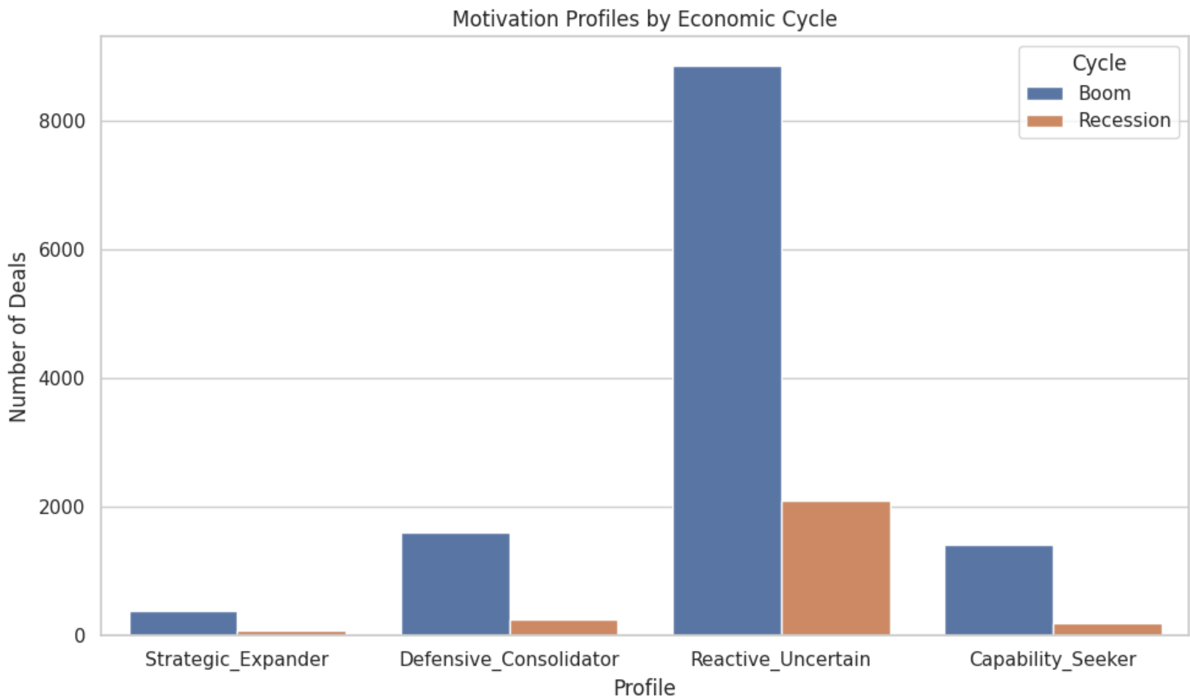

Fig 3 Distribution of motivation profiles across deals in both the datasets

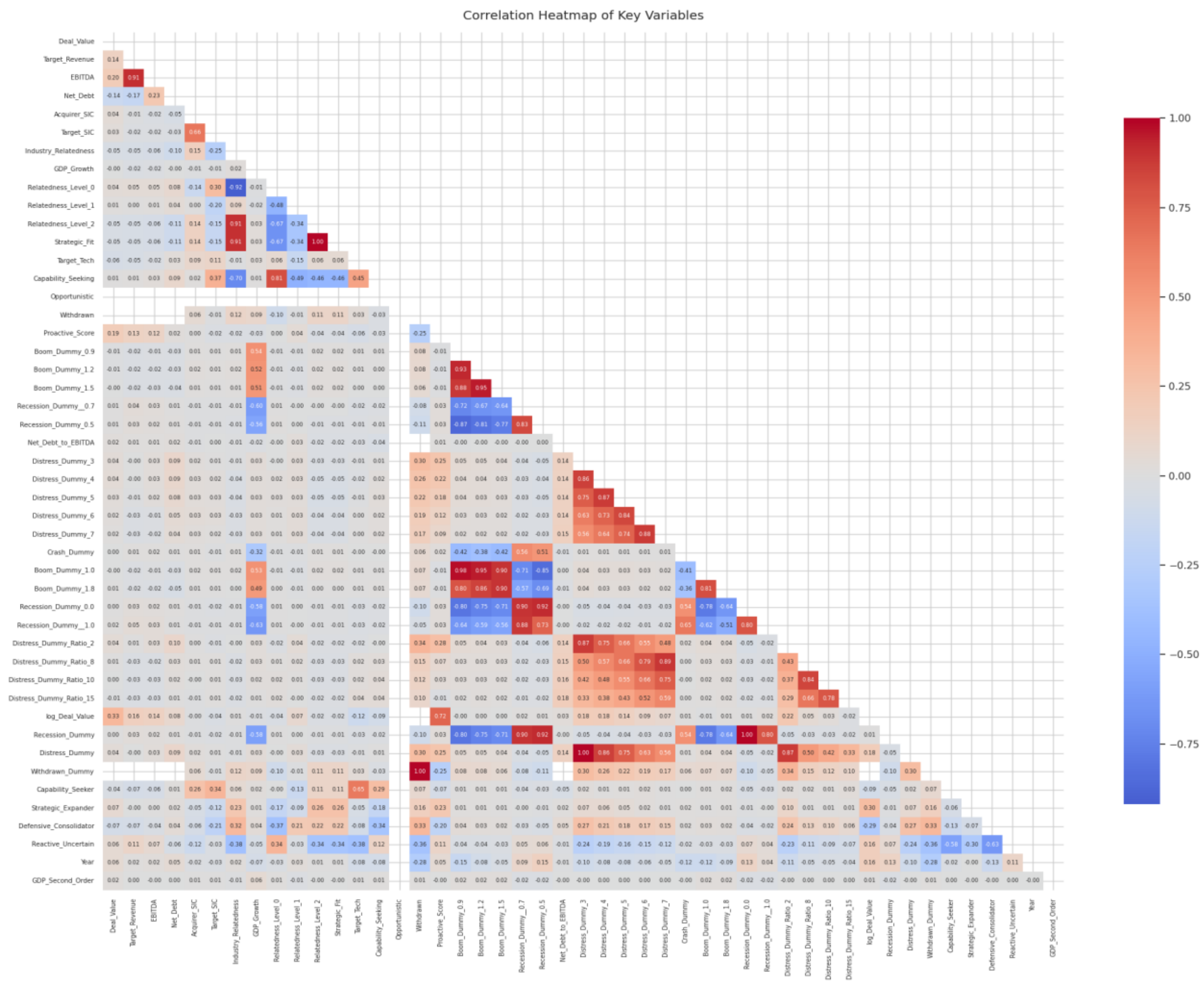

Fig.4 Correlation based heatmap of all the variables

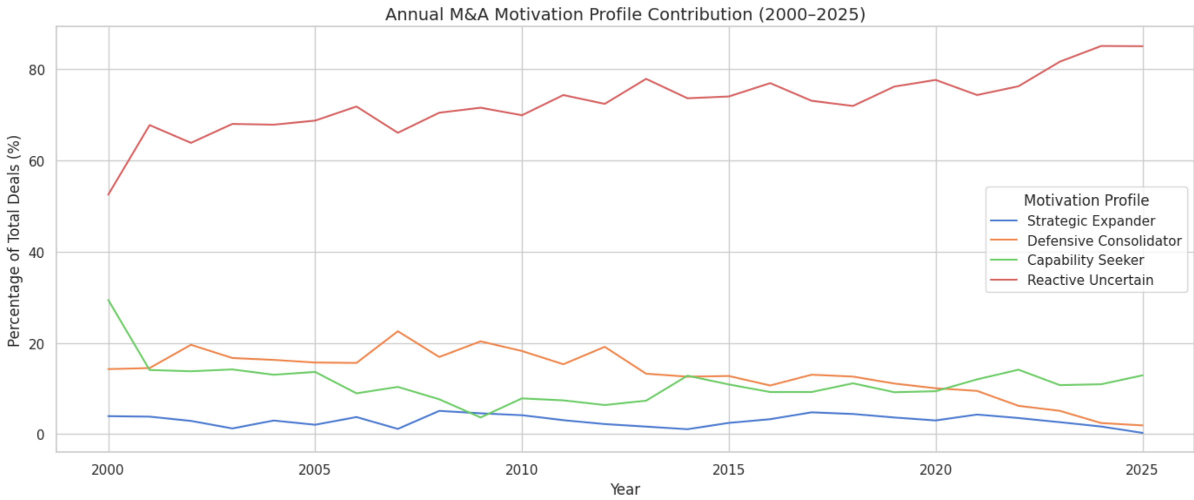

Fig. 5 Time series distribution of various motivation profiles in the main dataset

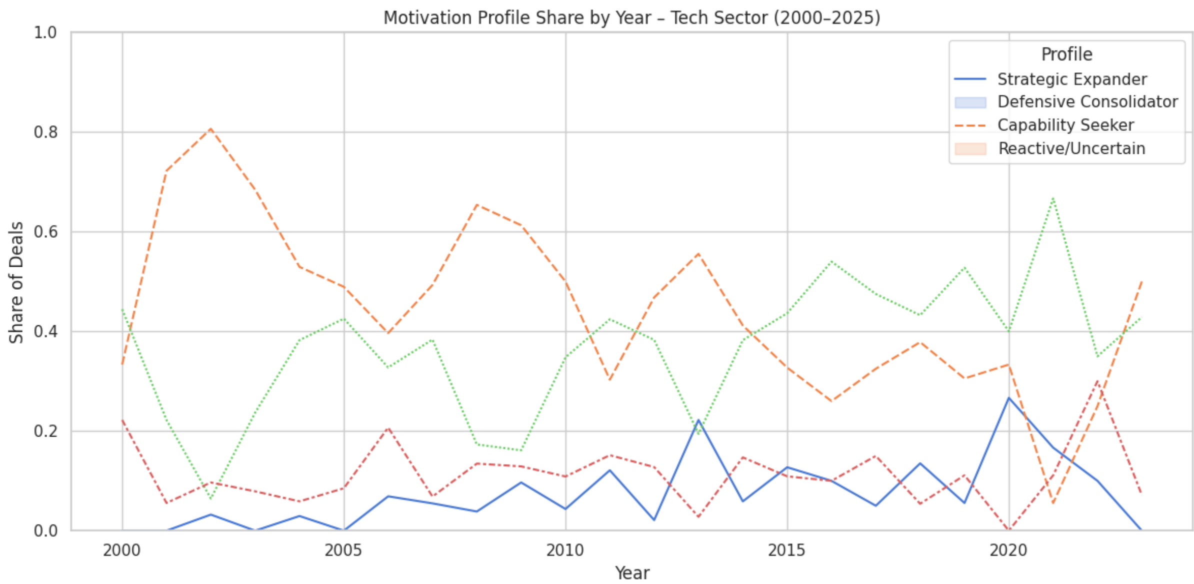

Fig. 6 Time series distribution of various motivation profiles in the tech deals dataset

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