Vertical Mergers as a Strategic Response to Economic Uncertainty: Evidence from U.S. M&A Activity (2006–2020)

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Abstract

This thesis investigates the impact of vertical and horizontal mergers and acquisitions on investor wealth, specifically focusing on how economic uncertainty influences merger behavior and outcomes. The study follows Fan & Goyal's (2006) methodology and distinguishes between vertical and horizontal mergers using input-output tables from the U.S. Bureau of Economic Analysis. The first hypothesis posits that economic uncertainty increases the proportion of vertical mergers. In contrast, the second explores whether vertical mergers generate higher abnormal returns in uncertain times compared to unrelated mergers. Using a sample of over 100,000 U.S. M&A transactions from 2006 to 2020, sourced from SDC Platinum, the research classifies mergers by vertical relatedness and applies event study analysis and multiple linear regression methodology. Findings reveal a consistent statistical relationship between economic health indicators (S&P 500 variations) and the proportion of vertical mergers. Furthermore, results from event studies and regression models suggest that vertical relatedness has a significant positive effect on CAAR during periods of economic instability, particularly from 2006 to 2010 and 2016–2020. The Economic Policy Uncertainty Index (EPUI) support the selection of instability periods and confirms the findings between economic instability, uncertainty and CAR variations. The study contributes to the M&A literature by demonstrating that vertical integration may serve as a strategic risk-mitigation tool during volatile economic conditions, delivering higher value to investors than horizontal mergers under similar circumstances.

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Introduction

Mergers and acquisitions (M&A) play a central role in corporate strategy, enabling firms to achieve growth, diversification, market penetration, and competitive advantage. While the motives behind M&A are diverse, the outcomes of such transactions remain highly contingent on contextual factors, including the structure of the deal and prevailing economic conditions. The difference in outcome between horizontal mergers, involving firms within the same industry, and vertical mergers, involving firms along a supply chain, is of growing interest, and numerous papers have focused on this topic. However, not a lot of interest was specifically directed toward the difference in outcome when those two types of mergers take place in an unstable economic environment. In times of economic volatility, firms often reassess their strategic priorities, placing greater emphasis on efficiency, stability, and risk mitigation. Transaction cost economics and property rights theory suggest that vertical integration can serve as a protective mechanism by reducing dependency on external suppliers, stabilizing input costs, and enhancing coordination. This raises a critical question: Do firms pursue vertical mergers more aggressively during uncertain economic periods, and do such mergers generate higher investor returns compared to horizontal deals under similar conditions? This thesis addresses those questions by examining the relationship between economic uncertainty and merger types. The dataset used in this paper is from 2006 to 2020 and includes extreme economic instability events such as the 2008 financial crisis and the COVID-19 pandemic. The objective of this paper is twofold.

—To determine whether economic uncertainty increases the proportion of vertical mergers among all M&A deals.

—To assess whether vertical mergers outperform other types of mergers in terms of cumulative abnormal returns (CAAR) during periods of economic instability.

To do so, this paper starts with an overview of past literature on the main differences in motives, outcomes, and strategies regarding vertical and horizontal M&As. A data and methodology section then explains where the data is coming from and how it was modified to suit the purpose of this paper. Finally, the paper ends with a result and conclusion section that explains the findings and gives recommendations for future studies.

Literature Review

As introduced by Coase (1937), the concept of transaction costs explains why individuals organize into firms rather than relying solely on market transactions. Coase argues that firms emerge to reduce the costs associated with market exchanges, such as searching for information, negotiating contracts, and enforcing agreements. By internalizing these transaction costs, firms can operate more efficiently than if they depended entirely on external market mechanisms. This internalization leads to vertical integration, where a company controls multiple stages of production or distribution, substituting market exchanges with internal processes within the firm's boundaries. Some of the transaction costs are the search and information costs associated with finding reliable suppliers, negotiating prices, and ensuring quality, which can be costly and time-consuming. The bargaining and contracting costs, which represent the uncertainty and negotiation that come with every transaction, can then be avoided. This was the first time the well-known "Make or Buy" theory was introduced.

Following Coase's work, Williamson (1975, 1985) took his theory and developed a systemic model explaining why and when companies should choose market transaction (outsourcing) and hierarchical governance (vertical integration). His model is based on three key factors. The transaction costs, the asset specificity, and the uncertainty and frequency (risk factor). In his model, Williamson proposes that a company should opt for a market instead of internalizing production when the transaction costs are cheaper than producing it internally; when the asset is not specific, meaning there are multiple suppliers that can provide it; the uncertainty is low, meaning the market operates efficiently and the price and quality are predictable; the suppliers can be easily switched if contracts fail. He also argues that asset specificity leads to higher transaction costs in market exchanges, as firms fear opportunistic behavior (the hold-up problem). It also creates a greater incentive to vertically integrate since governing such transactions within a firm reduces uncertainty and potential exploitation. This insight was a major advancement over previous economic theories, which assumed that firms operated in conditions of perfect competition with minimal coordination costs.

One of the first to test Williamson's theory with an empirical investigation was Masten (1984). By using firm-level data from the aerospace industry, Masten provided quantitative evidence that vertical integration is strongly correlated with transaction cost-related factors, especially asset specificity. In this basic model, Gi represents the institution, Gi* represents internal production and Ĝi represents market transaction, he summarizes the "make or buy" decisions as the formula:

$$Gi = Gi^* \qquad \text{if } Li^*(\omega i) < L(\lambda i, \omega i),$$

And

$$Gi = \hat{G}i \qquad \text{if } Li^*(\omega i) \geq L(\lambda i, \omega i),$$

Where Li* is the cost of maintaining production internally, and Li is the cost of market transaction, depicted as a function of the specificity (λ) and complexity (ω) of the transaction. His experiment indicated a general reluctance on the part of the company's administrators to internalize instead of going to the market. However, this reluctance is overcome when companies are exposed to specialized and complex assets, confirming Williamson's theory.

Another study intending to validate Williamson's theory would be Walker and Weber (1987). Based on empirical data from a major U.S. automobile manufacturer, analyzing 60 make-or-buy decisions for automobile parts procurement. The dataset includes components that were either produced in-house (make) or sourced externally (buy). The study focuses on how supplier competition and environmental uncertainty influenced these decisions. The variables used in their work include supplier competition, which is measured by the number of available suppliers, the environmental uncertainty captured through demand fluctuations and technological changes, and cost efficiency to control production cost differences. Logistic regression analysis is used to model the probability of a firm choosing to "make" rather than "buy" based on transaction cost factors. The analysis includes:

- **Independent variables**: Supplier competition, environmental uncertainty, and cost factors.
- **Dependent variable**: The firm's decision to either produce in-house or outsource the component.
- **Control variables**: Production scale, technological complexity, and firm-specific factors that could influence decision-making.

Their results show that when supplier competition is high, firms prefer to buy than make. They also show that when companies are under high environmental uncertainty, such as demand fluctuations or rapid technological change, they tend to vertically integrate to secure supply chains and reduce risk. Their study validates TCE by showing that firms integrate not just for cost efficiency but also to reduce uncertainty and avoid supplier risks.

Many other studies confirmed the importance of asset specificity by examining specific industries such as electricity generation (Joskow, 1985), aluminum (Stuckey, 1983), (François, 1988), forestry (Globerman & Schwindt, 1986), chemicals (Lieberman, 1991), and offshore oil gathering (Hallwood, 1991).

Grossman and Hart (1986) refined this idea by shifting the focus from transaction cost to the allocation of residual control rights. They argue that firms integrate not just to reduce transaction costs and mitigate supply risk but also to gain control over non-contractible investments. This led to a formal game-theoretical foundation to explain when integration creates efficiency gains or losses. This transition laid the foundation for the property rights theory (PRT). Following their idea, firms integrate vertically when owning assets, giving them greater bargaining power over relationship-specific investments.

The works of Lafontaine and Slade (2007), Joskow (2010), and Whinston (2003) add to the PRT theory by providing empirical and theoretical insights into how firms structure their boundaries to mitigate transaction costs, safeguard asset-specific investments, and enhance efficiency. These studies collectively highlight the significance of ownership allocation, supplier relationships, and competitive dynamics in determining whether firms choose to integrate vertically or rely on market transactions.

A recent document released by the Organisation for Economic Co-operation and Development (OECD, 2019) explores vertical mergers in rapidly evolving industries (particularly technology, media, and telecommunications) and finds that one key motive behind vertical integration is the potential for efficiency gains, particularly through better coordination between supply chain participants. The study explains how vertical M&As can help eliminate double marginalization, where firms at different levels of the supply chain set separate markups, increasing final consumer prices. By acquiring other companies at different levels of the supply chain, those extra markups can be internalized and give a competitive edge to the acquiring company.

Vertical mergers can also mitigate risks associated with procurement, quality control, and market fluctuations, as well as reduce costs. According to the American Bar Association (2019), Supply disruptions can arise due to geopolitical instability, trade restrictions, natural disasters, or supplier unreliability. By merging with a key supplier, firms ensure a steady flow of inputs without interruptions. This is particularly relevant in industries such as pharmaceuticals, automotive, and technology, where supply chain disruptions can cause production halts, increased costs, and lost revenues. A vertically integrated firm internalizes these supply relationships, reducing its reliance on external suppliers and mitigating the risk of production delays. Another significant advantage of vertical integration is price stability. When firms rely on third-party suppliers, they are exposed to fluctuating raw material costs, inflationary pressures, and market-driven price changes. By acquiring their suppliers, companies can lock in costs and better forecast long-term expenses.

Technological synergies, which represent the integration of complementary technologies, knowledge, and innovation capabilities that result in greater efficiency, cost savings, and enhanced competitive advantages, can also be a strong motive for vertical integration. When firms operate independently at different levels of the supply chain, R&D priorities may not align, leading to inefficiencies, duplicated efforts, and slower innovation cycles. By merging with upstream suppliers or downstream distributors, companies can integrate R&D activities, accelerating the development and deployment of new technologies. Another critical aspect of technological synergies in vertical M&As is ensuring seamless interoperability between different components in a supply chain. When a company acquires a supplier of key technological inputs, it can customize and refine the technology to fit its specific needs, leading to improved product quality, reliability, and efficiency. (Slade, 2021.)

A notable example is Tesla’s acquisition of battery manufacturers and energy storage companies. By integrating with firms specializing in battery technology, Tesla can design batteries that are specifically optimized for its electric vehicles (EVs), ensuring better range, performance, and cost efficiency. (Electric Autonomy Canada, 2019)

Although they agree that costs and synergies are important drivers of vertical M&A, Irwin et al. (2025) propose that firms engage in vertical integration first and foremost to expand their market presence, secure key distribution channels, and strengthen their competitive advantage. Companies that rely on third-party distributors often face uncertainties in pricing, shelf space, and brand visibility. By acquiring downstream distributors or retailers, firms can secure guaranteed market access for their products, ensuring higher sales volume and brand control. Moreover, by acquiring upstream suppliers, companies can restrict their competitors' access to critical supply chain components or distribution networks. By integrating key suppliers or distributors, firms can gain preferential access to essential inputs while limiting competitors' ability to source those same resources efficiently.

On the other hand, depending on the company's situation, horizontal mergers might be more appropriate. Some of the primary motives behind horizontal mergers and acquisitions are the ability to acquire a larger customer base and enter new geographical regions. When companies merge horizontally, they inherit an existing customer base, reducing the time and costs associated with customer acquisition efforts. By merging with a well-established competitor, firms can instantly boost their market share, increase revenue streams, and cross-sell products or services to a larger audience.

One of the most popular examples of this type of acquisition would be the acquisition of Instagram by Facebook in 2012. Facebook gained all of Instagram's followers and could immediately start pushing some advertising. The acquisition also allowed Facebook to enhance its mobile offerings and solidify its position in the social media landscape. (DePamphilis, 2013.)

Merging with a competitor also allows firms to accelerate expansion and overcome market entry barriers more efficiently than through organic growth, especially in new geographical regions.

Regarding horizontal mergers, Chamberlin (1933) contributed in many ways to our understanding of the motives behind horizontal mergers. Prior to his work, economic theory largely operated under the assumption of perfect competition and pure monopoly. He contributed to the recognition of a middle ground, where firms operate in markets characterized by product differentiation, pricing power, and strategic behavior. Chamberlin argued that firms operating in monopolistically competitive markets have some control over pricing due to product differentiation. However, they still face competitive pressure from similar products. Based on his theory, companies have an incentive to merge or acquire competitors to combine their brand strengths, improve differentiation, and establish a dominant presence in the market.

Bain (1956) furthered this theory by arguing that market structure is a primary determinant of firm conduct and performance. In markets where a few large firms dominate, competition is naturally restricted, allowing firms to engage in strategic mergers to consolidate power and limit new competition. He also argued that one of the primary motives behind horizontal mergers is market power accumulation. When firms merge, they reduce the number of industry competitors, which can lead to higher prices and restricted output. Bain was one of the first to explore barriers to entry. Merging with competitors allows the new entity to achieve cost advantages, strengthen brand recognition, and restrict access to essential suppliers and distributors, which makes it very difficult for new companies to enter the market.

Another groundbreaking article came out a few years later, introducing the market for corporate control theory. (Manne, 1965) In his article, Manne argues that mergers serve as a disciplinary mechanism, ensuring that inefficiently managed firms are taken over by more competent management teams. According to his theory, stock prices reflect managerial efficiency. When a firm's stock price declines due to poor management, it becomes an attractive acquisition target. External investors or rival firms recognize these undervalued firms and initiate takeovers, replacing ineffective leadership and implementing strategic changes to restore profitability. This process benefits shareholders by aligning managerial incentives with their financial interests as managers seek to maintain efficiency and avoid the risk of being replaced. Unlike earlier theories that viewed mergers primarily as a means of increasing market power, Manne highlights managerial inefficiency as a key driver of M&A activity, arguing that takeovers function as a market-driven correction for poor corporate governance.

Steiner (1975) adds to this theory and proposes reasons why companies with inefficient management teams can be an interesting target for competitors. One of the many reasons highlighted in his work is the utilization of net operating losses (NOLs). A profitable firm can merge with a financially weak firm with large, accumulated tax losses, allowing the new entity to offset taxable income. It can also allow them to restructure asset depreciation to reduce immediate tax liabilities. Another reason mentioned is stock market speculation and financial engineering rather than fundamental business improvements. Managers may merge with firms that have overvalued stock to create the illusion of corporate growth, which would inflate earnings per share (EPS), making the firm look more profitable.

A great example of a firm being acquired by an external investor for management inefficiency and undervalued stock is the purchase of Twitter by Elon Musk in October 2022. Shortly after the acquisition, Musk fired more than half the company's employees, stating that it was overstaffed and inefficient. The transaction was highly controversial, and many argued that Musk only bought the platform for personal reasons. Fidelity Investments published a valuation report in 2024 stating that the company was now worth less than a fifth of its pre-acquisition value. (Rush, 2024)

Marris (1968) Published a theory proposing that some mergers are indeed motivated by personal interests. Managers driven by personal ambitions such as increased compensation, prestige, and power may pursue mergers to expand the firm's size and influence, even when such actions do not align with shareholder interests.

Meckling and Jensen (1976) add to this theory by introducing the agency theory as a key determinant of M&A outcomes, arguing that conflicts of interest between managers and shareholders influence the success of acquisitions. They suggested that managers who do not fully bear the financial consequences of their decisions may pursue mergers for personal benefits, such as increased control and compensation, rather than for shareholder value maximization.

This perspective highlights a potential divergence between managerial goals and shareholder value, suggesting that some mergers are motivated more by the desires of managers to build corporate empires than by the pursuit of economic efficiencies or market power. Since mergers have multiple motivations, it's hard to determine whether efficiency, tax, or managerial motives dominate and the impact of each on merger's success.

Even if the motives behind the M&A are in line with shareholder interests, the result can be harmful to the consumer. As explained by Williamson (1968, 1975) in his trade-off hypothesis, mergers reduce the number of competitors in a market, giving the merged firm greater pricing power. With fewer firms, there is a higher risk of collusion or monopolistic behavior, leading to higher prices and reduced output. Consumers may face reduced product choices and lower service quality. However, he argued that if the efficiency gains outweigh the potential price increase caused by the concentration of market power, the merger can still be justified. His work introduced a balanced approach that weighs efficiency gains against market power effects, which later influenced antitrust regulation and corporate merger strategies.

To help understand the reasons and motives behind M&A, Porter (1980) created a five forces model that analyzes the industry's structure and helps assess if a horizontal M&A is the course of action to take.

1. Industry rivalry—if the competition is intense in the industry, a merger would eliminate some competitors and increase market concentration.
2. The threat of new entry—if it's easy for companies to enter the market and steal market share, mergers would increase economies of scale and raise entry barriers.
3. Bargaining power of suppliers—if suppliers have a lot of influence over firms, mergers will increase their bargaining power, allowing them to negotiate better input costs.
4. Bargaining power of buyers—when consumers ask for lower prices, mergers enhance the pricing power of firms and reduce buyer influence.
5. The threat of substitutes—when lots of alternative products are available, it threatens to reduce demand. Mergers allow firms to expand product lines and reduce substitution risks.

In contrast, Tirole (1988) approaches horizontal mergers from a microeconomic and game-theoretical perspective, focusing on market structure, firm behavior, and regulatory implications. His model differentiates between pro-competitive and anti-competitive mergers, assessing whether a merger leads to efficiency gains or increased market power. Tirole expands on Bertrand's (1883) and Cournot's (1863) competition models by demonstrating that horizontal mergers can either intensify competition (if rivals lower prices to defend market share) or enable collusion (if the reduced number of firms makes coordination easier). He also highlights entry deterrence strategies, where merged firms use their increased market power to raise barriers to entry, limit access to key resources, or engage in predatory pricing to eliminate smaller competitors.

In a recent paper, Feldman & Hernandez (2021) explore the different types of synergies and how they are created. The internal synergies by the efficiency gain from combining operation, the market power synergies by the reduced number of firms, the relational synergies by improving stakeholder relations, the network synergies by combining networks and connections, and the non-market synergies that arise from other variables.

Since the motives for undertaking horizontal and vertical M&A are not the same, it's legitimate to wonder if they lead to similar results. Chatterjee (1986) provides an early framework for understanding how horizontal and vertical mergers create value through different types of synergies. His study categorizes synergies into operational, financial, and collusive and finds that horizontal mergers primarily generate operational and collusive synergies, leading to cost efficiencies and increased market power. In contrast, vertical mergers create value through financial synergies and transactional efficiencies by improving coordination along the supply chain. His findings suggest that horizontal mergers benefit from economies of scale, while vertical mergers enhance resource allocation and integration.

By testing the same hypothesis but in the banking sector, Houston (2001) **s**uggests that horizontal mergers provide higher cost savings due to operational synergies, which directly contribute to improved profitability. Vertical mergers in banking do not yield substantial cost savings, but they enhance revenue stability by reducing dependence on external suppliers or distributors. Fee (2004) confirms in his study that horizontal mergers can lead to improved productive efficiency and enhanced buying power. According to him, these gains are primarily attributed to economies of scale, increased market share, and strengthened bargaining positions with suppliers and customers.

Hackbarth and Morellec (2008) found similar results by analyzing stock returns surrounding M&A announcements to assess how the market values horizontal and vertical mergers differently. Their study finds that horizontal mergers tend to generate larger positive abnormal stock returns upon announcement, reflecting investor optimism about cost reductions and market dominance. However, they caution that these gains are often short-term, as post-merger integration challenges can erode expected benefits. Conversely, vertical mergers exhibit a more neutral market reaction, as they do not immediately alter competitive market structure but can improve long-term cash flows through better supply chain coordination and risk reduction. Those results are in line with Bhuyan (2002), who states that vertical mergers may fail to create significant differential advantages.

Contrary to those articles, Sonenshine (2022) finds that while abnormal returns to targets are similar between vertical and horizontal mergers, the gains to targets relative to acquirors are significantly higher in vertical mergers (53.6% versus 39.5%). This suggests that investors perceive vertical mergers as offering greater relative benefits to target firms compared to acquirers. Some of the reasons used to justify this result are improved bargaining power, supply chain control and mitigate the risks associated with supply chain disruptions, price fluctuations and external shocks.

Hypothesis Development I

The mixed results in past research are not conclusive on which type of M&A yields better results post-transaction. However, as mentioned previously, in vertical M&As, the acquirer will often merge with a supplier or a distributor to mitigate certain risks and gain more control of its supply chain. Conversely, when firms engage in horizontal mergers, it is usually to gain market share, increase efficiency, spend excess free cash flow, etc. Consequently, I believe that in times of economic uncertainty, we should see a higher volume of vertical mergers since managers will try to shield the company against uncertainty instead of taking on more risk with new challenges.

For those reasons, my first hypothesis is,

H_0: There is no relation between the economy's health and the proportion of vertical mergers.

H_1: In times of economic uncertainty, the proportion of vertical mergers increases.

Even though motives are important, there are many other variables that influence the success of mergers and acquisitions. Ball and Brown (1968) conducted one of the earliest empirical studies on how financial information influences market reactions to corporate events, including M&As. They argued that market participants react to the quality and transparency of financial disclosures, making financial reporting a key determinant in post-merger performance.

Jensen (1986) argues that when firms have excess cash, managers may invest in suboptimal projects or pursue acquisitions that do not enhance shareholder value. He notes that firms with high free cash flow and low growth opportunities are more likely to engage in value-destroying acquisitions. Additionally, he observes that leveraged buyouts (LBOs) and takeovers often target such firms, as the increased debt burden post-acquisition serves to discipline managerial spending and align interests with shareholders.

Straub (2007) separates the determinants of M&A success into three categories. The strategic logic, which includes market similarities, potential market power and potential purchasing power. Organizational integration, which includes the relative size and cultural compatibility. Financial considerations, which include the acquisition premium and du diligence.

In their comprehensive study on the long-term determinants of M&A's success, Renneboog and Vansteenkiste (2018) identified that CEOs who have successfully completed previous acquisitions may develop overconfidence, leading them to pursue additional deals without adequate due diligence. This overconfidence can result in overpayment for targets or the selection of unsuitable acquisition candidates, ultimately harming long-term performance. They also mentioned the relatedness and complementarity between the acquiring and target firms as a key factor. Acquisitions are more likely to succeed when there is a high degree of relatedness in terms of industry, products, or markets between the acquirer and the target. Those results confirm Peter and

Howard's (1986) theory that related diversification is more likely to generate positive returns than unrelated diversification, aligning with resource-based and synergy theories. Their findings support the argument that firms should pursue mergers that leverage existing core competencies rather than expanding into unrelated industries.

Some of the factors that influence the success and quantity of M&A are not specific to the entities involved but rather to macroeconomic variables such as interest rates, inflation, and GDP growth. In her 2024 study titled "The Influence of Macroeconomic Factors on Mergers and Acquisitions and Stock Market Performance." Lakra (2024) examines how key macroeconomic variables, specifically GDP growth, interest rates, inflation, and unemployment rates, affect corporate strategies and investor behavior. She finds a strong correlation between GDP growth and the increase in M&A activity. High inflation would also correlate with an increase in M&A activity to achieve an economy of scale in harder times. In contrast, high interest rates seem to be negatively correlated with M&A activity. Röhrer et al. (2023) confirmed those results and found that bond yields and past real GDP growth are robust quantitatively and statistically significant determinants of mergers and acquisitions.

Antunes (2017) focuses on M&A activity in the United Kingdom from 1985 to 2015, analyzing the role of GDP growth, stock market performance, and financial stability. The study uses a time-series econometric approach, incorporating Vector Autoregression (VAR) and Granger causality tests to examine the short- and long-term relationships between macroeconomic variables and M&A activity. Antunes finds that GDP growth is a strong driver of M&A activity, suggesting that firms are more likely to engage in acquisitions during economic expansions when corporate earnings and market confidence are high. However, stock market performance appears to have a weaker impact compared to the U.S., indicating that equity market fluctuations do not always drive M&A waves in the UK.

Garita and Van (2007) did similar research but expanded the analysis to cross-border M&As, examining 211 countries between 1986 and 2005 to identify key macroeconomic determinants influencing international acquisitions. Using panel data regression models, the study assesses the role of financial openness using the Chin-Ito index as a proxy, economic development using gross GDP per capita as a proxy, and exchange rate stability in cross-border M&A activity. The findings suggest that financial openness is a crucial factor, as countries with liberalized financial markets experience higher inbound M&A transactions. Additionally, economic development positively correlates with M&A activity, as wealthier economies attract more foreign investment. Exchange rate stability also plays a significant role, with stable currencies making target firms more attractive to foreign acquirers.

Hypothesis Development II

Since higher interest rates make it harder for companies to borrow, higher inflation means uncertainty in prices; lower GDP means lower demand and higher unemployment rates mean an unsteady workforce; securing the supply chain through those economic situations is a priority and, in theory, should reward companies that are able to do so. For those reasons, my second hypothesis is:

H_0: The abnormal returns around the announcement date are not impacted by the vertical linkage between bidders and targets.

H_1: In times of economic uncertainty, mergers with vertically related bidders and targets yield better abnormal returns

One of the challenges in testing those hypotheses is the differentiation between horizontal and vertical mergers. Since data banks like SDC don't separate them, we need to classify them ourselves. Even if a significant portion of the literature uses SIC classification (Morck et al., 1990), (Berger, 1995), (Gugler et al., 2003) and (Alhenawi, 2015), the classification of mergers as vertical based solely on SIC codes relies on the assumption that different but related SIC codes imply a supply chain relationship. However, SIC codes do not explicitly capture input-output linkages between industries. As a result, this method is based on inferred relationships and may be less precise.

One of the most reliable ways to differentiate vertical and horizontal mergers is by using the industry's commodity flow information in input-output (IO) tables. Many previous papers used IO-based methodology to determine vertical relatedness, such as Fan and Lang (2000), Caves and Bradburd (1988) and Lemelin (1982). IO-based methodology has also been used to determine vertical relatedness in merger studies such as Mc Guckin et al. (1991) and Matsusaka (1996).

In this paper, I will follow the Fan and Goyal (2006) methodology to classify my data. More specifically, I use commodity flow information in (IO) tables to calculate the vertical relatedness coefficient and then determine which industries are vertically related. Once all the industries are sorted, I will be able to classify every M&A transaction between vertical and horizontal mergers. This process will be explained in more detail in the data and methodology section.

Data

I decided to use target and bidder companies from the United States (U.S.) to conduct my research to limit the number of transactions in my data sample and to avoid cross-country effects. To test if the proportion of vertical mergers increases in times of economic uncertainty, I first had to determine what could represent uncertainty in an economic context. I decided to use the Gross Domestic Product (GDP), S&P500 and the Economic Policy Uncertainty (EPU) as economic health indicators. After looking at the historical data, I identified two distinct periods where those indicators were significantly lower than usual. The first period is from 2006 to 2010, which includes the global financial crisis, and the second period is from 2016 to 2020, which includes the beginning of the COVID-19 pandemic. I will use the period between 2011 and 2015 to represent the regular state of the economy were the GDP, EPU and S&P500 were stable. For example, over the two periods of economic uncertainty the average Yearly GDP growth was -1.15% while 0.05% for the stable period. For the EPU, the average variation is 4% during the uncertainty periods and only 1% in the stable period.

I then downloaded all the M&A transactions between U.S. acquire and target companies from 2006 to 2020 on SDC Platinum. In the SDC request, I also asked for an announcement date, the effective date, the date withdrawn, the target's name, the target's SIC code, the target's industry, the target's nation, the acquirer's name, the acquirer's industry, the acquirer's nation, the acquirer's SIC code, the status of the transaction, the percentage of shares acquired, the percentage of shares owned after the transaction, the value of the transaction, the payment method, if the companies were public or private and if the acquirer is a financial firm. The first data sample was composed of 144,133 transactions. I cleaned the data by removing all the transactions with a withdrawn date, incomplete transactions, those with no date effective, and those with hedge fund involved. Finally, I deleted all the transactions with the same acquirer and target name since those are composed mostly of restructuring, intra-company mergers, parent company absorbing subsidiaries, etc. The resulting data sample was composed of 121,058 transactions from 2006 to 2020.

To classify the mergers between vertical and horizontal, I followed the methodology of Fan and Goyal (2006) and downloaded the Use Table from the Bureau of Economic Analysis (BEA). The Use Table, also known as the Input-Output (IO) table, was first published by the DEA in the early 1950s. Its main purpose is to reveal the dependencies among certain sectors. It is also used by the government to help understand the impact of subsidies and natural catastrophes. It is also used by economists to simulate different sector growth impacts.

As it is presented by the BEA, the use table is a matrix containing the value of commodity flows between 407 intermediate industries. Let's call each pair of industries *i* and *j*. The table reports the dollar value of its output required to produce industry's j's total output, which we will call a_{ij}. By dividing a_{ij} by the total value of industry's j's output, we get V_{ij}, which represents the dollar value of industry's i's output required to produce 1 dollar's worth of industry's j's output. By doing the same thing but by dividing a_{ji} by the total value of the industry's i's output, we get V_{ji}, which represents the dollar value of the industry's j's output required to produce one dollar's worth of the industry's i's output. The relatedness coefficient represents the highest input requirement for each pair of industries denoted as (= max ($V_{ij,}$ V_{ji})) and measures to which extent industry j and I are vertically related. For example, if we take the millwork industry, I, and the office and commercial structures industry j, from the 2017 use table, we can see that industry j (office and commercial structures) requires 2,555 million dollars worth of industry I (millwork) to produce a total output of 79,023 million dollars. By dividing 2,555 million by 79,023 million, we can determine that industry j (office and commercial structures) requires 0.032 dollars of industry I (millwork) output to produce one dollar of output. Conversely, industry I (millwork) requires 1,840 million of industry j's (office and commercial structures) output to produce a total of 16,379-million-dollar outputs, which means industry I requires 0.11 dollars to produce 1 dollar worth of output. In this example, the vertical relatedness coefficient for this pair of industries would be 0.11, which is the maximum of the two industries' requirements.

Since my M&A data started in 2006 and ended in 2020, I used the 2007 IO tables to classify transactions from 2006 to 2010, the 2012 IO tables for 2011 to 2015, and the 2017 IO tables for 2016 to 2020.

Once the vertical relatedness of each pair of industries was determined, it could be used to determine which M&A transactions were vertical and which were horizontal. But before doing so, since the target and acquirer industry are classified using SIC and the Use Matrix is classified in IO, some conversions needed to be done. I downloaded the SIC to NAICS crosswalk available on the NAICS's website. While converting the classification code, I realized SDC platinum sometimes customizes the SIC classification by placing a letter at the end of the code. For example, code 619A has the description "Real Estate; Mortgage Bankers and Brokers." I thought the "A" could be removed, but the description of Industry 619 is "Other Telecommunications Activities." In total, 1,508 transactions (8 different industries) had customized codes for the target company. To classify them properly, I used the industry description and asked ChatGPT to give me the corresponding SIC code, which I verified and changed manually. Unfortunately, SDC platinum does not differentiate between companies in the electric, gas, and water distribution and classifies all of them into a custom 499A SIC code. Since there were only 476 transactions using this code for the target, I decided to eliminate them from the data since it would be impossible to determine their respective vertical relatedness. I also eliminated the "Unclassifiable Establishments" SIC code 9999. I did the same process to assign the proper SIC code to the acquirer company.

To go from NAICS to IO classification, I first used the BEA industry and community codes and NAICS concordance available on the BEA website. In this list, the NAICS codes have 2, 3, 4, 5, or 6 digits instead of the classic 6-digit code, which makes it laborious to convert into IO. By using this table and V-lookup in Excel, I was able to associate 19,531 target industries with their respective IO code, which represents roughly 18% of the total number of targets in my dataset. Since using this method would mean I would lose 80% of my dataset, I tried another way.

Considering NAICS and IO codes are built similarly, both the first two digits represent the economic sector and industry subsector, and both the third and fourth digits represent the industry groups; I associated them manually by reading both their industry descriptions on the BEA's concordance table guided by the first four digits. I manually converted 974 different NAICS codes to IO codes and was able to associate 109,538 target industries with their respective IO code, which represents roughly 99% of the targets. To make sure my conversion was adequate, I compared, for the same target, the IO code I got by running a V-lookup in Excel and the IO code I assigned manually, and on the 19,531 targets, 100% were identical. I then did the same process for the acquirer companies to get a dataset of 109,377 transactions.

Once I had the IO code for both target and acquirer, it was time to put my M&A data and my vertical relatedness coefficient data together. To do so, since the IO relatedness coefficient was in a matrix, I had to modify it so it could be merged with the M&A data. Using Power Quarry, I created a custom 2-column table. In the first column, I put both IO industries separated by a hyphen, and in the second column, the vertical relatedness. Then, I created a column in the M&A dataset merging both the target and acquirer's IO code again separated by a hyphen so I could use V-Lookup to have their corresponding vertical relatedness. I then used the V-Lookup function to associate all the transactions from 2006 to 2010 with the 2007 vertical relatedness coefficients, transactions from 2011 to 2015 with the 2012 coefficients, and 2016 to 2020 with the 2017 coefficients.

Following the Fan and Goyal (2006) methodology, I decided to use a 5% cutoff. Mergers with a vertical relatedness coefficient greater than 5% will be considered vertical. This cutoff was also used in McGuckin (1991) and Matsusaka (1993). From 2006 to 2020, a total of 16,865 mergers had a vertical relatedness coefficient greater than 5% and are considered vertical. **Figure I** illustrates the cumulative distribution of the vertical relatedness from 2006 to 2020. As we can see, 85 percent of the transactions had a vertical relatedness coefficient smaller than equal to 5%. It is interesting to notice that 2 percent of the transactions had a vertical relatedness coefficient greater than 25%, meaning that more than 2,000 pairs of acquirers and targets got 25% of their supply from the same industry.

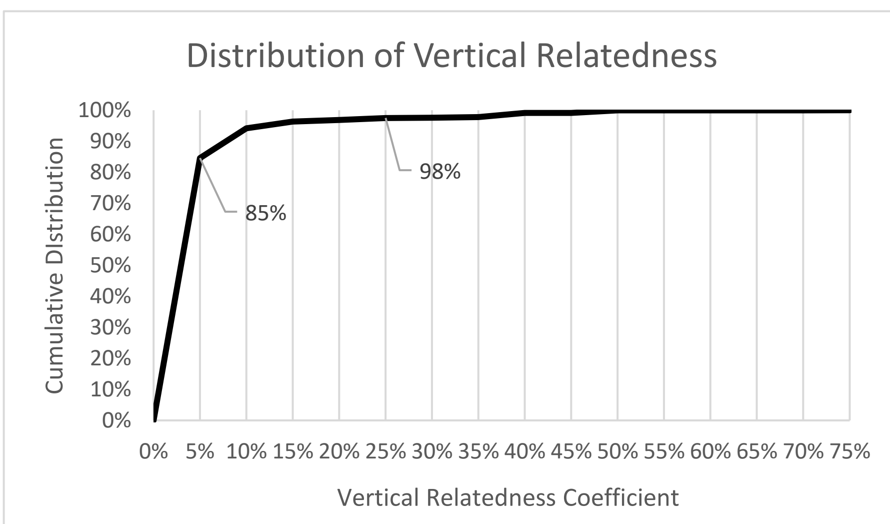

Figure I – Cumulative Distribution of 109,377 Mergers' Vertical Coefficient from 2006 to 2020

I also tested if the IO table's year had an impact on vertical classification. To do so, I calculated the number of transactions with a vertical coefficient greater than 5% using only the 2017 IO table as a reference and got 17,620 vertical mergers. Since there would be more vertical mergers using only the 2017 IO table, it means that companies concentrated on their supply chain between 2007 and 2017. Following this result, I calculated the percentage of the transaction's vertical coefficient that had a variation greater than 10% throughout the different tables. From 2007 to 2012, 25% of the vertical coefficient changed by more than 10%; from 2012 to 2017, 28%, and from 2007 to 2017, 26%. For the same periods, only 29% of the coefficient stayed the same from 2007 to 2012 and from 2012 to 2017, but only 19% from 2007 to 2017. Those results indicate that some industries tend to maintain the same distribution of suppliers, while others have high variations in theirs.

To test my first hypothesis, I needed to see if the vertical merger proportion increased with the economic uncertainty.

Methodology and Results

Hypothesis I

To see if the proportion of vertical mergers increases in times of economic instability, I ran four different ordinary least square "OLS" regressions. All the regressions have the proportion of vertical mergers as the dependent variable, an economic indicator, and a dummy for time periods (1 if the transactions were between 2006-2010 and 2016-2020) as independent variables. The first model used annual GDP variation (Macrotrends, n.d.) and the EPU, the second the quarterly GDP variation (Bureau of Economic Analysis [BEA], n.d.) and the EPU, the third the annual S&P500 variation (Macrotrends, n.d.) and the EPU and the fourth the monthly S&P500 variation (Investing, n.d.) and again the EPU. In Table 1, model 1, we can see that the annual GDP variation is not statistically significant, with a p-value of 0.87, the EPU and the time period dummy are also not significant. We can also see that when the number of observations increases in model 2, the variables seem to be even less significant. In models 3 and 4, the same pattern is observable. By going from 15 to 180 observations, the significance gets worst.

Table No. 1 - OLS of Economic Instability Indicators on Vertical Merger Proportion

Variables	Model 1	Model 2	Model 3	Model 4
Intercepts	-0.12570 (0.1466)	-0.01306 (0.6644)	-0.14600 (0,1318)	0.01176 (0.5874)
GDP	-0.00114 (0.9614)	0.00271 (0.3235)		
S&P500			0.16115 (0.6355)	-0.07682 (0.7883)
Time period	0.14166 (0.2243)	0.02829 (0.4438)	0.13104 (0,2628)	0.00026876 (0.9919)
Economic Policy Uncertainty	0.81864 (0.6213)	-0.03856 (0.8228)	1.30030 (0.4925)	0.02006 (0.7277)
Observation	15	60	15	180

This table shows 4 OLS with proportion variation in vertical mergers as their dependent variable. It presents each OLS' parameters estimate and their respective p-value in parentheses. The variables complete descriptions are presented in the Appendix. The statistical significances are presented by $, *. ** and ***, which respectively represent 0.10, 0.05, 0.01, and 0.001 significance level.

Since the significance of the variable worsen when the number of observations increases, I tested to see if the model was appropriate for the data. I ran model 1 and asked for the minimum and maximum predicted values and got -0.12074 and 0.09697. Since the dependent variable is a proportion and can only be between 0 and 1, I realized the model was not adequate for the data. I reran the regressions, using the fractional logit model this time since it only allows predicted values to be between 0 and 1.

Table No.2 - Fractional Logit Regression of Economic Instability Indicators on Vertical Merger Proportion

Variables	Model 1	Model 2	Model 3	Model 4
Intercepts	-2.0521 (0.0001)***	-2.0629 (0.0001)***	-1.9745 (0,0001)***	-2.0557 (0.0001)***
GDP	0.0011 (0.7918)	-0.0016 (0.3261)		
S&P500			-0.6346 (0.0001)***	-0.4956 (0.011)**
Time period	0.5398 (0.0001)***	0.5000 (0.0001)***	0.5793 (0,0001)***	0.4939 (0.0001)***
Economic Policy Uncertainty	-1.3560 (0.0001)***	-0.0573 (0.4912)	-3.0551 (0.0001)***	-0.0085 (0.8233)
Observation	15	60	15	180

This table shows 4 Fractional Logit regression with proportion variation in vertical mergers as their dependent variable. It presents each OLS' parameters estimate and their respective p-value in parentheses. The complete descriptions of the different variables are presented in the Appendix. The statistical significances are presented by $, *. ** and ***, which respectively represent 0.10, 0.05, 0.01, and 0.001 statistical significance.

As we can see in Table 2, the time period variable is statistically significant at a 99,9% confidence level for all models. Interestingly, according to models 1 and 2, the GDP variation is not a good indicator of vertical merger variation. The S&P500, on the other hand, is highly statistically significant at a 99% and 99,9% confidence level. As we know, the GDP is calculated using household consumption, investment, government spending, exports, and imports. It represents the economic health, but not necessarily the financial market's health. Furthermore, we can also see that the EPU variable is only significant when there is a low number of observations. Since companies base their decisions on the impact on their bottom line, it makes sense that the S&P500, which is a direct indicator of their profitability, is a better explanatory variable than the GDP and EPU.

The negative coefficient for the S&P500 indicates a higher proportion of vertical merger when the S&P500 decreases. The positive coefficient for the time period dummy also indicates an increase in vertical mergers when the mergers take place in uncertain economical periods.

Those results allow us to reject the null hypothesis and conclude that in times of economic uncertainty, the proportion of vertical mergers increases.

As theorized in the hypothesis, the main reason why companies would prioritize vertical mergers during economic instability periods is to ensure their supply by acquiring key players alongside their supply chain.

Hypothesis II

Event Study

To test my second hypothesis: In times of economic uncertainty, mergers with vertically related bidders and targets yield better abnormal returns, I decided to follow the same reasoning as Fan and Goyal (2006) and use the event study methodology. Since they separated their data into pure vertical, pure horizontal, vertically related, mixed vertical and horizontal, and diversifying mergers, and I only separated my data into vertically related at 5% cutoffs, I decided to introduce another control in the event study. Following Lys and Yehuda's (2011) reasoning, private targets create more synergies than public targets because they have more intangible assets. Jaffe al. (2015) also found that bidders acquiring private targets tend to have higher abnormal returns around the announcement dates caused by the reduced competition and lower acquisition premiums. Capron and Shen (2007) also arrived at the conclusion that private targets were a better buy since they gave access to the acquisition of valuable private information and resources, which also led to higher abnormal returns around the announcement date.

Based on those papers, I decided to separate my data into four subgroups: Public Bidders, which represent all the transactions, including a public bidder. Public Bidder and Private Target, which represents only the transactions between the public bidder and private targets. Public Bidder Vertically Related to Target, which represents the transaction including a public bidder vertically related to its target at a 5% cutoff, and Public Bidder Vertically Related to Private Target, which is the same as the previous subgroup, only for private targets. In the annex, those subgroups are referred to as Panel A, B, C, and D, respectively. Since the objective is to see if the abnormal returns for the vertically related bidder and target are better in the economic uncertainty period, the subgroups are separated into 3 periods. From 2006 to 2010, from 2011 to 2015, and from 2016 to 2020. As in the first hypothesis section, the 2006-2010 and 2016-2020 periods are economically uncertain.

From the previous 109,377 transactions, I assigned the 8-digit CUSIP to the bidders and removed transactions with unavailable CUSIP. The final data sample used for the event study before being separated into periods were 14,547 for Panel A, 9,254 transactions for Panel B 2,436 transactions for Panel C and 1,395 transactions for Panel D.

I ran the event studies on Eventus and determined the event windows as: 5 days prior, 1 day post announcement date, 1 day prior to 1 day post announcement date, 1 day prior to 5 days post announcement date, 5 days prior to 5 days post announcement date, 1 day prior to 30 days post announcement date and 2 to 30 days post announcement date.

Table No.3 - Event Study Summary for interval (-1, +1) for each panel and time period

Intervals	Panel	N	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Portfolio Time-Series t	Uncorrected Patell z	Generalized Sign z
2006-2010								
(-1,+1)	A	4287	0.59%	0.37%	2228:2059>>>	7.572***	7.529***	5.025***
(-1,+1)	B	2679	0.47%	0.31%	1396:1283>>>	4.716***	5.003***	4.163***
(-1,+1)	C	943	0.60%	0.45%	504:439>>>	3.304***	4.196***	3.256***
(-1,+1)	D	586	0.40%	0.40%	322:264>>>	1.832*	2.962**	3.269***
2011-2015								
(-1,+1)	A	4305	0.77%	0.51%	2294:2011>>>	13.409***	13.352***	6.207***
(-1,+1)	B	2798	0.67%	0.44%	1495:1303>>>	8.808***	9.076***	5.164***
(-1,+1)	C	492	1.20%	0.86%	273:219>>>	5.511***	7.162***	3.114***
(-1,+1)	D	251	0.98%	0.75%	144:107>>	2.820**	4.477***	2.931**
2016-2020								
(-1,+1)	A	3772	0.81%	0.36%	2038:1734>>>	10.906***	7.994***	5.823***
(-1,+1)	B	2429	0.95%	0.42%	1333:1096>>>	10.253***	7.572***	5.476***
(-1,+1)	C	628	1.26%	0.61%	360:268>>>	5.590***	5.177***	4.044***
(-1,+1)	D	335	1.92%	0.88%	208:127>>>	7.449***	5.649***	4.693***

This table presents the cumulative abnormal returns (CARs) and statistical tests from interval (-1, +1) around announcement date. Panel A represents the subset of public bidders, Panel B represents public bidders purchasing private target, Panel C Public bidders vertically related to their target and Panel D public bidders vertically related to their private targets. Full tables for each period are presented in the Appendix.

By looking at the tables from 2006 to 2010 (appendix), we can see that the mean cumulative abnormal returns are stable throughout the different Panels. For the interval (-1,+1), the minimum is 0.40% and the maximum is 0.60%. Even if the portfolio time series-t and uncorrected Patell z are statistically significant at a 99.9% confidence level, there is no significant difference between the different panels. Moreover, all the Panels show positive CAAR for the first 4 intervals and negative CAAR for the last 2.

In the tables from 2011 to 2015 (appendix), all the panels also had positive CAAR for the first four intervals and negative CAAR for the last 2. However, Panel C and D have significantly higher CAAR than Panel A and B. Intervals (-1,+1) and (-5,+5), for example, are at 0.77% and 0.71% for Panel A and 0.67% and 0.65% for Panel B while the CAAR for the same intervals are at 1.20% and 1.15% for Panel C and 0.98% and 1.36% for Panel D. This indicates that for this period, mergers between vertically related bidder and target have a more positive impact on the investors around announcement date.

In tables from 2016 to 2020 (appendix), we can see that vertically related bidders and targets seem to have a higher CAAR than the others. In Panel A, public bidders, the CAAR for intervals (-1,+1) and (-5,+5) are 0.81% and 0.89% as in Panel C, public bidders vertically related to their target, the CAAR for the same intervals are 1.26% and 1.24%. The same difference can be observed between Panel B and D. In Panel B, the CAARs for the previously mentioned periods are 0.95% and 0.97%, while in Panel D, those CAARs are 1.92% and 2.05%.

The higher CAAR for transactions between vertically related bidder and target is in link with the findings of Fan and Goyal (2006) for the same intervals.

For the interval (-1, +1) the range for tables from 2006 to 2010 is 0.40% to 0.60%. For the tables from 2011 to 2015 0.67% to 1.2% and for the tables from 2016 to 2020 0.81% to 1.92%. Even if the CAARs seem to be higher in the last period, we don't have enough statistical evidence to reject the null hypothesis.

Regression

By looking at those event studies, it is impossible to determine to which extent the vertical relation between bidder and target influences the abnormal returns around the announcement date, but it is clear vertical dependence has a significant impact. The impact of bidders only acquiring private companies is also unclear. One of the reasons the results are not concluding is perhaps caused by the lack of control for deals and company specifics. To control for these effects, I use an OLS regression model.

From the previous 109,378 mergers, I found the bidder's CUSIP and left out those unavailable. I used the M&A data from SDC available on WRDS to find cumulative abnormal returns (-10, +10) to the announcement date, as did Fan and Goyal (2006). In their paper, they use vertical merger dummies, pure vertical, pure horizontal, vertical horizontal, a dummy for the method of payment, a dummy for size, a dummy for the industry, and for the year. I did the same thing, but instead of using multiple variables for vertical relatedness, I directly used the vertical coefficient, and instead of using dummies for the transaction value, I used the actual amount. For the year dummy, I used a dummy that takes 1 when the transaction is either between 2006 and 2010 or between 2016 and 2020 to represent my economic instability periods.

CAAR = Vertical Coefficient + Same SIC code + Transaction Value + Method of Payment + Time Period

Since the CAAR and the Vertical Coefficient are significantly smaller numbers than the other variables, I multiplied them by 100. Inversely, since the transaction value and the premium are significantly larger than the rest of the data, I used the log of the transaction value, and I divided the premium by 10 to get more meaningful coefficients in the OLS.

The regressions presented in Table 5 are based on a dataset of 602 transactions that took place between 2006 and 2020. Their descriptive data is presented in Table 5 and the complete description of each variable is presented in the Appendix. As we can see, all the continuous variables have a massive difference between their mean and their median, which indicates the presence of outliers. Furthermore, 99% of the bidders acquired more than 50% of the targets, and 100% of the targets kept in this sample were public. Since the Control of Target equals almost 100% and the Target is public equals 100%, we can assume that they will be insignificant.

Table No. 4 - Descriptive Table for Regressions Presented in Table 5

Continuous Variables	Mean	Median	Standard Error	Min	Max
Vertical Coefficient (%)	0,04	0,02	0,08	0	0,72
Transaction Value ($)	2366,17	600,05	5759,5	3,32	67285,7
Premium (%)	68,23	32,38	564,39	-76,67	13720,73
Economic Policy Uncertainty (%)	0,03	-0,01	0,216685	-0,47	0,98
Dummy Variables	**Proportion**				
Same SIC code	62%				
Control of Target	99%				
Payment Method	60%				
Target is Public	100%				
Friendly	99%				
Time Period Dummy	69%				

This table presents the descriptive data of the 602 transactions used to run the regression presented in Table 5. The Variables descriptions are presented in the appendix.

In Table 5 Model 1, we can see that the p-value for the vertical coefficient is not statistically significant, but the Period variable is significant at a 95% confidence level. Even though the model is statistically significant at a 99.9% confidence level, I believe some variables could be worthwhile to add, such as the 4 weeks prior to the announcement, the deal attitude, if the bidder acquired control of the target, and if the target is a private or public company. Many articles, such as Fish et al. (2024), use the 4 weeks prior to the announcement as a control when looking at CARS since a significant portion of the abnormal returns were realized before the announcement of the merger (Augustin et al. 2019).For the deal's attitude, as introduced by Wansley et al. (1983), hostile takeover results in more volatility and lower CARs for the acquirer. In a more recent study, Renneboog and Vansteenkiste (2019) show that hostile takeovers tend to underperform in the short and long term due to integration and overpayment. Bidders that acquire more than 50% of the target companies pay a premium to gain control. This is explored by Moeller et al. (2005) in their paper on the 1980 M&A wave. The reason why a public or private target matter was explained in the Event Study part of this paper. For all those reasons and because those are widely accepted control variables, I decided to include them in the model. Furthermore, I created a dummy that takes 1 when the transaction takes place in one of the two economic instability periods (2006–2010, 2016–2020) and an interaction term that multiplies the vertical coefficient by the period dummy.

Table No. 5 – Regressions Models of Instability and Vertical Relation on CAAR

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Intercept	6.42517 (0.0016)**	1.90432 (0.8606)	-0.30835 (0.9552)	7,24314 (0,0002)***
Vertical Coefficient	0.09983 (0.1325)	0.00101 (0.9932)		
Same SIC Code	0.83125 (0.4198)	0.66924 (0.5175)		
Control of Target		8.22705 (0.1405)	8.05901 (0.1404)	
Transaction Value	-2.26425 (0.0003)***	-2.44227 (0.0002)***	-2.42988 (0.0002)***	-2,22485 (0,0004)***
Payment Method	1.86486 (0.0642)$	2.08624 (0.0405)*	1.99478 (0.0475)*	1,93753 (0,0527)$
Target is Public		1.27088 (0.8810)		
4 weeks Premium		-0.00943 (0.2767)		
Friendly		-4.07956 (0.4123)		
Time Period Dummy	-2.36845 (0.0244)*	-2.89603 (0.0130)*	-2.98244 (0.0068)**	-2,44543 (0,0296)*
Interaction term		0.13852 (0.3275)	0.15241 (0.0494)*	0,14941 (0,0536)$
Economic Policy Uncertainty				-0.17797 (0,0284)*
Observations	602	602	602	602
Model Significance	(0,0005)***	(0,0025)**	(0,0002)***	(>0,0001)***

This table shows 4 OLS with CAARs -10 and +10 days from the announcement date as their dependant variable. It presents each OLS' parameters estimate and their respective p-value in parentheses. The complete variable descriptions are presented in the Appendix. The models are based on 602 observations from 2006 to 2020. The statistical significances are presented by $, *. ** and *** which respectively represents the statistically significance 0.10, 0.05, 0.01 and 0.001.

As we can see, Model 2's statistical significance is less than that of Model 1, probably due to a high correlation between variables. We can also see that the variables previously significant are no longer. To find the best version of the model, I used the Proc glmselect in SAS Studio and Akaike Information Criterion (AIC) to get the most explanatory power with the lowest number of variables possible. This test adds and removes variables one by one to find the best combination of independent variables to explain the variation in the CAAR.

As we can see in Model 3, the p-value is the best so far. We can also see that the variable with the most explanatory power is the transaction value with a p-value of 0.0002, followed by the dummy, which represents if the transaction is in a period of economic uncertainty with a p-value of 0.0068. The method of payment and the interaction term are also statistically significant at a 95% confidence level. The reason why Proc glmselect kept the Control of Target variable even though it is not statistically significant is because it improves the prediction power of the model.

To make sure the time period variable captured the economic instability, I reran model 2, but this time including the EPU. By using the stepwise selection process again, I arrived at model 4. As we can see, the only difference between model 3 and 4 is the replacement of the insignificant variable Target Control by the significant variable EPU. Since the EPU coefficient is highly negative and significant, this confirms that the economic period really captured the economic instability and we can confidently conclude that in time of economic uncertainty, the CAAR are lower, but vertical mergers perform better than other types of mergers.

Since the parameter estimate of the interaction term is positive 0.15241 and statistically significant, we can reject the null hypothesis and conclude that mergers between vertically related bidders and targets yield better abnormal returns in times of economic uncertainty. We can also see that the time period dummy parameter is negative, which indicates that transactions taking place in the economic uncertainty periods have lower CARS. Same for the transaction value. The higher the transaction value, the lower the CAR. On the contrary, transactions paid in cash increase the CAR.

Conclusion

This thesis set out to explore how vertical and horizontal mergers impact investor wealth, particularly under conditions of economic uncertainty. By applying a rigorous classification method based on input-output industry tables and using an extensive dataset of over 100,000 U.S. M&A transactions from 2006 to 2020, the study aimed to test two key hypotheses: whether economic uncertainty increases the proportion of vertical mergers and whether vertically related mergers yield higher abnormal returns during these periods.

The analysis found a consistent statistical relationship between the economic indicator S&P 500 variation and the proportion of vertical mergers.

More notably, the event studies and regression analyses confirmed that vertical relatedness has a significant and positive effect on cumulative abnormal returns (CAR) during periods of economic instability. Furthermore, those results were test proofed by using the EPU to account for economic uncertainty. These findings support the idea that vertical integration acts as a risk-mitigation strategy, enhancing investor confidence and firm value when economic conditions are volatile by securing the supply chain.

The thesis also contributes to M&A literature by reinforcing the importance of deal structure and timing. While horizontal mergers may provide efficiency and market power in stable environments, vertical mergers appear more resilient in downturns, likely due to enhanced supply chain control, reduced dependency, and coordination benefits.

Future research could include the distinction between horizontal mergers, diversifying mergers, and vertical mergers to see how they each react to different economic circumstances.

In conclusion, this study highlights the intrinsic role that vertical linkages play in shaping merger and acquisition outcomes.

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Appendices

Appendix A: Variable Descriptions

Variables	Descriptions
GDP	The Gross Domestic Product (GDP) variable represents the yearly variation for table 1 and 2 model 1, and the quarterly variation for table 1 and 2 model 2.
S&P500	The S&P500 variable represents the yearly variation for table 1 and 2 model 3 and the monthly variation for table 1 and 2 model 4.
Time Period	The time period variable is a dummy that takes 1 when the transactions take place between 2006 and 2010 and between 2016 and 2020 which are the two uncertainty periods.
Economic Policy Uncertainty	The Economic Policy Uncertainty (EPU) is 3 component variables that describes the economic uncertainty. The first component is a news-based serie that scans for specific uncertainty words, the second component draws from congressional budget office reports that compile lists if temporary federal tax code provision and the last component draws from reports from the Federal Reserve Bank of Philadelphia's survey of professional forecasters.
Vertical Coefficient	The Vertical Coefficient represents the total use of 407 different commodities by 407 different industries divided by the total output of the same industry. This coefficient represents the vertical relatedness between bidders and target. Each pair of industries with a vertical coefficient greater that 5% is considered vertically related. The coefficient was multiplied by 100 for presentation and interpretation purposes.
Same SIC Code	Dummy that takes 1 when bidder and target have the same SIC code.
Control of Target	Dummy that takes 1 when the bidder acquires mode that 50% of the target's total shares.
Transaction Value	The transaction value variable is the transaction value log for presentation and interpretation purposes
Payment Method	The Payment method is a dummy that takes 1 when the bidder paid more that 50% of the price in cash.
Target is Public	Dummy that takes 1 when the target is publicly traded
4 Weeks Premium	The 4 weeks premium represents the percentage of cumulative abnormal return for the bidder 4 weeks prior to the announcement date
Friendly	Dummy that takes 1 if the transaction attitude is friendly
Interaction Term	The interaction term variable is the result of the time period dummy multiplied by the vertical coefficient.

Appendix B: Event Study Tables

2006 to 2010

The tables presented in Panel A show the mean cumulative abnormal return (CAR) for the bidders from 2006 to 2010 depending on the time interval specified in the column "Days," in which 0 represents the date of the merger announcement. The abnormal returns presented in the table below will be used to determine if vertical relatedness impacts abnormal returns around the announcement date in times of economic uncertainty. The portfolio time-series t determines if the abnormal returns are significant; the uncorrected Patell z represents the null hypothesis that the mean abnormal return is zero and corrects for cross-sectional correlation. The generalized sign z indicates if the number of positive and negative abnormal returns is significantly different than in normal circumstances. The symbols $, *, **, and *** denote statistical significance at 0.10, 0.05, 0.01, and 0.001, and the symbols (<,>) show the general direction of the one-tailed test.

Panel A: Market Model Abnormal Returns, Equally Weighted Index, Public Bidders 2006–2010

Intervals	N	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Portfolio Time-Series t	Uncorrected Patell z	Generalized Sign z
(-5,+1)	4287	0.56%	0.31%	2157:2130>>	4.693***	4.228***	2.855**
(-1,+1)	4287	0.59%	0.37%	2228:2059>>>	7.572***	7.529***	5.025***
(-1,+5)	4287	0.73%	0.47%	2243:2044>>>	6.106***	6.349***	5.484***
(-5,+5)	4287	0.70%	0.42%	2186:2101>>>	4.660***	4.505***	3.742***
(-1,+30)	4287	-0.04%	-0.08%	2131:2156>	-0.161	-0.504	2.060*
(+2,+30)	4287	-0.64%	-0.45%	2047:2240	-2.605**	-2.951**	-0.507

Panel B: Market Model Abnormal Returns, Equally Weighted Index, Public Bidders & Private Target 2006–2010

Intervals	N	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Portfolio Time-Series t	Uncorrected Patell z	Generalized Sign z
(-5,+1)	2679	0.36%	0.21%	1333:1346>	2.370**	2.175*	1.727*
(-1,+1)	2679	0.47%	0.31%	1396:1283>>>	4.716***	5.003***	4.163***
(-1,+5)	2679	0.68%	0.49%	1410:1269>>>	4.542***	5.134***	4.705***
(-5,+5)	2679	0.58%	0.38%	1362:1317>>	3.051**	3.218***	2.848**
(-1,+30)	2679	0.04%	-0.11%	1329:1350>	0.134	-0.564	1.572$
(+2,+30)	2679	-0.42%	-0.42%	1278:1401	-1.376$	-2.201*	-0.400

Panel C: Market Model Abnormal Returns, Equally Weighted Index, Public Bidders Vertically Related to Target 2006–2010

Intervals	N	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Portfolio Time-Series t	Uncorrected Patell z	Generalized Sign z
(-5,+1)	943	0.48%	0.36%	474:469)	1.724*	2.195*	1.300$
(-1,+1)	943	0.60%	0.45%	504:439>>>	3.304***	4.196***	3.256***
(-1,+5)	943	0.69%	0.54%	494:449>>	2.490**	3.277***	2.604**
(-5,+5)	943	0.57%	0.45%	467:476	1.637$	2.172*	0.844
(-1,+30)	943	-0.53%	-0.33%	478:465>	-0.904	-0.965	1.561$
(+2,+30)	943	-1.13%	-0.78%	456:487	-2.012*	-2.364**	0.127

Panel D: Market Model Abnormal Returns, Equally Weighted Index, Public Bidders Vertically Related to Private Targets 2006–2010

Intervals	N	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Portfolio Time-Series t	Uncorrected Patell z	Generalized Sign z
(-5,+1)	586	0.18%	0.24%	288:298	0.541	1.184	0.458
(-1,+1)	586	0.40%	0.40%	322:264>>>	1.832*	2.962**	3.269***
(-1,+5)	586	0.42%	0.50%	303:283>	1.264	2.437**	1.698*
(-5,+5)	586	0.20%	0.34%	286:300	0.483	1.342$	0.292
(-1,+30)	586	-0.81%	-0.67%	294:292	-1.126	-1.575$	0.954
(+2,+30)	586	-1.21%	-1.07%	279:307	-1.772*	-2.607**	-0.286

2011–2015

The tables presented in Panel A show the mean cumulative abnormal return (CAR) for the bidders from 2011 to 2011, depending on the time interval specified in the column "Days," in which 0 represents the date of the merger announcement. The abnormal returns presented in the table below will be used to determine if vertical relatedness impacts abnormal returns around the announcement date in times of economic uncertainty. The portfolio time-series t determines if the abnormal returns are significant; the uncorrected Patell z represents the null hypothesis that the mean abnormal return is zero and corrects for cross-sectional correlation. The generalized sign z indicates if the number of positive and negative abnormal returns is significantly different than in normal circumstances. The symbols $, *, **, and *** denote statistical significance at 0.10, 0.05, 0.01, and 0.001, and the symbols (<,>) show the general direction of the one-tailed test.

Panel A: Market Model Abnormal Returns, Equally Weighted Index, Public Bidder 2011–2015

Intervals	N	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Portfolio Time-Series t	Uncorrected Patell z	Generalized Sign z
(-5,+1)	4305	0.78%	0.50%	2277:2028>>>	8.891***	8.539***	5.688***
(-1,+1)	4305	0.77%	0.51%	2294:2011>>>	13.409***	13.352***	6.207***
(-1,+5)	4305	0.70%	0.47%	2280:2025>>>	7.989***	7.919***	5.780***
(-5,+5)	4305	0.71%	0.45%	2272:2033>>>	6.462***	6.156***	5.536***
(-1,+30)	4305	-0.05%	0.06%	2163:2142>	-0.279	0.459	2.212*
(+2,+30)	4305	-0.82%	-0.46%	2011:2294<<	-4.606***	-3.823***	-2.423**

Panel B: Market Model Abnormal Returns, Equally Weighted Index, Public Bidder & Private Target 2011–2015

Intervals	N	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Portfolio Time-Series t	Uncorrected Patell z	Generalized Sign z
(-5,+1)	2798	0.72%	0.45%	1487:1311>>>	6.182***	6.131***	4.862***
(-1,+1)	2798	0.67%	0.44%	1495:1303>>>	8.808***	9.076***	5.164***
(-1,+5)	2798	0.60%	0.39%	1476:1322>>>	5.163***	5.224***	4.445***
(-5,+5)	2798	0.65%	0.40%	1483:1315>>>	4.450***	4.318***	4.710***
(-1,+30)	2798	-0.14%	0.01%	1411:1387>	-0.579	0.082	1.987*
(+2,+30)	2798	-0.81%	-0.43%	1325:1473	3.441***	-2.842**	-1.266

Panel C: Market Model Abnormal Returns, Equally Weighted Index, Public Bidders Vertically Related to Target 2011–2015

Intervals	N	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Portfolio Time-Series t	Uncorrected Patell z	Generalized Sign z
(-5,+1)	492	1.19%	0.88%	279:213>>>	3.557***	4.788***	3.656***
(-1,+1)	492	1.20%	0.86%	273:219>>>	5.511***	7.162***	3.114***
(-1,+5)	492	1.16%	0.88%	272:220>>	3.492***	4.774***	3.024**
(-5,+5)	492	1.15%	0.90%	263:229>	2.744**	3.887***	2.212*
(-1,+30)	492	-0.85%	-0.29%	244:248	-1.186	-0.730	0.498
(+2,+30)	492	-2.05%	-1.15%	212:280<<	-3.018**	-3.070**	-2.388**

Panel D: Market Model Abnormal Returns, Equally Weighted Index, Public Bidders Vertically Related to Private Targets 2006–2010

Intervals	N	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Portfolio Time-Series t	Uncorrected Patell z	Generalized Sign z
(-5,+1)	251	1.33%	1.00%	145:106>>	2.510**	3.920***	3.057**
(-1,+1)	251	0.98%	0.75%	144:107>>	2.820**	4.477***	2.931**
(-1,+5)	251	1.00%	0.82%	143:108>>	1.897*	3.232***	2.804**
(-5,+5)	251	1.36%	1.08%	137:114>	2.043*	3.367***	2.046*
(-1,+30)	251	-1.92%	-0.56%	126:125	-1.698*	-1.023	0.657
(+2,+30)	251	-2.90%	-1.30%	110:141<	-2.691**	-2.514**	-1.364$

2016–2020

The tables presented in Panel A show the mean cumulative abnormal return (CAR) for the bidders from 2016 to 2020 depending on the time interval specified in the column "Days," in which 0 represents the date of the merger announcement. The abnormal returns presented in the table below will be used to determine if vertical relatedness impacts abnormal returns around the announcement date in times of economic uncertainty. The portfolio time-series t determines if the abnormal returns are significant; the uncorrected Patell z represents the null hypothesis that the mean abnormal return is zero and corrects for cross-sectional correlation. The generalized sign z indicates if the number of positive and negative abnormal returns is significantly different than in normal circumstances. The symbols $, *, **, and *** denote statistical significance at 0.10, 0.05, 0.01, and 0.001, and the symbols (<,>) show the general direction of the one-tailed test.

Panel A: Market Model Abnormal Returns, Equally Weighted Index, Public Bidders 2016–2020

Intervals	N	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Portfolio Time-Series t	Uncorrected Patell z	Generalized Sign z
(-5,+1)	3772	0.77%	0.30%	1984:1788>>>	6.797***	4.360***	4.065***
(-1,+1)	3772	0.81%	0.36%	2038:1734>>>	10.906***	7.994***	5.823***
(-1,+5)	3772	0.93%	0.42%	1994:1778>>>	8.119***	6.136***	4.390***
(-5,+5)	3772	0.89%	0.36%	1971:1801>>>	6.203***	4.207***	3.641***
(-1,+30)	3772	0.30%	-0.28%	1814:1958<	1.246	-1.745*	-1.472$
(+2,+30)	3771	-0.51%	-0.63%	1744:2027<<<	-2.199*	-4.400***	-3.736***

Panel B: Market Model Abnormal Returns, Equally Weighted Index, Public Bidder & Private Target 2016–2020

Intervals	N	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Portfolio Time-Series t	Uncorrected Patell z	Generalized Sign z
(-5,+1)	2429	0.87%	0.35%	1306:1123>>>	6.173***	4.153***	4.380***
(-1,+1)	2429	0.95%	0.42%	1333:1096>>>	10.253***	7.572***	5.476***
(-1,+5)	2429	1.04%	0.42%	1286:1143>>>	7.358***	4.877***	3.568***
(-5,+5)	2429	0.97%	0.34%	1265:1164>>	5.440***	3.249***	2.716**
(-1,+30)	2429	0.71%	-0.05%	1168:1261	2.350**	-0.162	-1.220
(+2,+30)	2429	-0.24%	-0.48%	1136:1293<<	-0.829	-2.605**	-2.519**

Panel C: Market Model Abnormal Returns, Equally Weighted Index, Public Bidders Vertically Related to Target 2016–2020

Intervals	N	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Portfolio Time-Series t	Uncorrected Patell z	Generalized Sign z
(-5,+1)	628	1.11%	0.57%	337:291>	3.211***	3.120***	2.208*
(-1,+1)	628	1.26%	0.61%	360:268>>>	5.590***	5.177***	4.044***
(-1,+5)	628	1.40%	0.87%	338:290>	4.053***	4.796***	2.288*
(-5,+5)	628	1.24%	0.83%	324:304	2.876**	3.610***	1.170
(-1,+30)	628	0.16%	-0.12%	295:333	0.218	-0.413	-1.144
(+2,+30)	628	-1.10%	-0.73%	279:349<<	-1.569$	-2.099*	-2.421**

Panel D: Market Model Abnormal Returns, Equally Weighted Index, Public Bidders Vertically Related to Private Targets 2006–2010

Intervals	N	Mean Cumulative Abnormal Return	Precision Weighted CAAR	Positive: Negative	Portfolio Time-Series t	Uncorrected Patell z	Generalized Sign z
(-5,+1)	335	1.80%	0.89%	198:137>>>	4.559***	3.761***	3.601***
(-1,+1)	335	1.92%	0.88%	208:127>>>	7.449***	5.649***	4.693***
(-1,+5)	335	2.17%	0.99%	183:152>	5.511***	4.165***	1.961*
(-5,+5)	335	2.05%	1.01%	172:163	4.142***	3.373***	0.759
(-1,+30)	335	0.80%	-0.03%	155:180	0.947	-0.099	-1.099
(+2,+30)	335	-1.12%	-0.91%	142:193<<	-1.401$	-1.921*	-2.519**