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Shifting tides in M&A financing: analyzing transformations in M&A financing structures in a post-Covid era

Master Thesis

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Abstract

This paper investigates the impact of the post-Covid financing climate on M&A financing structures to assess if (or the magnitude of) a reallocation among specific financing instruments has occurred. The results indicate that there is a significant reduction in the employment of debt financing in M&A investments in the post-Covid era compared to the pre-pandemic period. Furthermore, this effect is demonstrated to be homogeneous across industries. However, it cannot be determined that the reduction in debt financing is offset by an increase in cash- and equity-based funding. In addition, it is found that the reduced reliance on debt financing is stronger in unstable industries compared to stable industries. Also, an increased employment of equity financing in unstable industries has been established, potentially due to risk mitigation considerations. This paper utilized a sample of 3,295 transactions by US acquirers over the period 2013 – 2023. The results are obtained by performing an OLS and 2SLS regression model with robust standard errors.

Keywords: Mergers and Acquisitions, Method of Payment, Covid-19, Sectoral Variation, Macroeconomic Influences

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List of abbreviations

2SLS	Two-Stage Least Squares
ADF	Augmented Dickey-Fuller
BLUE	Best Linear Unbiased Estimators
BvD	Bureau van Dijk
CAGR	Compound Annual Growth Rate
CBOE	The Chicago Board Options Exchanges
CCI	Consumer Confidence Index
CPI	Consumer Price Index
ESG	Environmental Social Governmental
FFR	Federal Funds Target Rate
GDP	Gross Domestic Product
GFC	Global Financial Crisis
GS	Government Spending
IV	Instrumental Variable
M&A	Mergers and Acquisitions
Market cap	Market capitalization
MoP	Method of Payment
OLS	Ordinary Least Squares
p.p.	percentage points
S&P500	Standard and Poor's 500
SIC	Standard Industrial Classification
US	United States
USD	United States Dollar
VIF	Variance Inflation Factors
VIX	Volatility Index
WHO	World Health Organization
WRDS	Wharton Research Data Services
y-o-y	year-on-year

1. Introduction

The ever-evolving realm of Mergers and Acquisitions (M&A) has consistently captivated the interest of both academics and practitioners due to its significant influence on corporate strategies and the global economic structure. M&A transactions, distinguished by their irreversible nature and high economic significance, serve as critical moments in a firms' lifespan by influencing its operational efficiency, competitive positioning and growth trajectory (Andrae et al., 2001). The significance of these corporate investments extends beyond the firm itself by influencing a broad array of stakeholders, including investors, regulatory bodies and national economies. While most scholars investigate the "why" and "when" of the transaction, studying the "how" holds at least equivalent importance (Mulherin et al., 2017). Vladimirov (2015) highlights this by stating that bidder financing strategies in M&A deals should be a first-order determinant. Amidst these findings, the financing structure of the M&A transaction is considered to be a critical facet, fundamentally shaping the deal's outcome and post-transaction integration process. Financing mechanisms, including debt, cash and equity and its strategic employment carries distinct implications for tax considerations, risk allocation and corporate control dynamics. Myers & Majluf's (1984) Pecking-Order Theory offers a foundational background, indicating a financing hierarchy driven by a company's cost of capital and the information asymmetry inherent in its operations. This theoretical framework highlights the strategic considerations inherent in financing decisions and further underscores the complex interplay between internal funding conditions and external capital market environments. The period after the Covid-19 pandemic has been characterized by large alterations in the macroeconomic climate, including enhanced government spending, increasing inflation and subsequent rising interest rates. These alterations significantly altered the context in which M&A transactions took place. Consequently, a re-examination of traditional financing structures in M&A investments is paramount, leading to the following research question:

How have alternations in the macroeconomic climate in the post-pandemic period influenced the financing structure of M&A investments?

This paper examines how the financing composition of M&A deals has been impacted by the changing financing climate in the aftermath of the Covid-19 pandemic. In light of strong alternations in the financing climate, this study tries to identify the extent to which these macroeconomic changes have reshaped the financing composition of M&A activities. By utilizing data from 3,295 transactions by US acquirers from 2013 – 2023, this study tries to assess whether (or the magnitude of) a reallocation among specific financing instruments such as cash, debt and equity has indeed occurred. Additionally, this study aims to explore the differential impact of these changes across various sectors. As such, this study contributes to the existing M&A and Method of Payment (MoP) literature in several ways. Firstly, to the best of my knowledge, this paper pioneers the effect of alternations in the post-Covid financing climate on M&A financing strategies. By delving into this unexplored period, this study enriches our understanding of corporate adaptability and resilience in the face of large global disruptions. Secondly, this study extends the conventional MoP literature by integrating the impact of macroeconomic shifts on M&A financing strategies, thereby offering a more holistic view of the interplay between global economic developments and corporate finance strategies. Lastly, while the existing body of literature primarily differentiates between cash- and equity-based funding, this study places a significant focus on debt financing as a crucial component of M&A funding. This setup not only extends our current understanding of financing mechanisms considered but also emphasizes the nuanced roles these mechanisms play in strategic corporate investments, in particular in response to a volatile economic climate.

The empirical results reveal a significant reduction in debt financing in the post-Covid era after controlling for endogeneity. This consistency suggests that the post-pandemic financial climate did significantly diverge from traditional debt financing, however, it cannot be established that this divergence was offset by an increase in cash- or equity-based funding. When extending the original analysis to identify a potential differential impact across various industries, no significant results can be observed. Consequently, it can be concluded that the shift in financing structures is homogenous across sectors. In addition, it can be argued that unstable sectors are more susceptible to changes in the macroeconomic climate and hence should see larger alterations in their financing structures in response to economic disruptions. This analysis confirms this notion by showing that unstable sectors have a more pronounced shift to lower debt reliance in comparison to unstable sectors after controlling for endogeneity. It should be noted that the significant negative relationship between the proportion of debt financing and the post-Covid period is only introduced after controlling for endogeneity within the original OLS model. The appearance of such a significant relationship when alternating the statistical model employed highlights the complexity of the relationship between financing structures in M&A and a period characterized by large macroeconomic upheaval and underscores the need for further investigation in this everchanging field. From a practical standpoint, the findings of this paper point towards corporate adaptability in financing strategies amidst economic disruptions, in addition to highlighting the complex interplay between corporate finance strategies and macroeconomic policy. Moreover, the more heightened responsiveness of firms in unstable industries may prompt policymakers and financial institutions to consider tailored programs to support industries that are particularly sensitive to economic turbulence.

The remainder of this paper is structured as follows: Section 2 presents the literature review, highlighting the fundamental principles in M&A financing and examining how these can be influenced by (macro)economic disruptions. Section 3 proceeds to formulate the hypotheses that serve as the foundation for the research undertaken in this study. Section 4 describes the dataset employed for this study as well as the descriptive statistics of this dataset. Section 5 presents the overall research methodology and several tests to identify the applicability of this research design. Section 6 delineates the empirical results, inclusive of several robustness checks. Finally, Section 7 concludes the paper, discusses its inherent limitations and proposes avenues for further research.

2. Literature review

2.1 Defining M&A

M&A are among the largest, most pivotal of corporate investments, well-known for their irreversible nature and their high economic significance (Andrade et al., 2001). In addition, the transactions are fundamental to the interests of investment bankers, securities lawyers, government regulators, employees and lobbyists. An extensive empirical literature in finance has been motivated by the number of transactions, the value of transactions, variability in deal premiums and structures, the search for understanding the causes and effects of M&A transactions and the involvement of multiple parties in these transactions (Mulherin et al., 2017). The basic questions investigated in M&A literature mostly relate to the "why" and the "when", i.e., why do these types of transactions occur, when do they happen and what are the (economic) effects of these types of investments (Mulherin et al., 2017).

Early research from Jensen & Ruback (1983) reviews much of the scientific literature on the market for corporate control. The evidence indicates that corporate takeovers generate positive gains, that target firm shareholders benefit and that bidding firm shareholders do not lose. They find that the gains created by corporate takeovers do not appear to come from the creation of market power. Yet, the Jensen & Ruback (1983) survey also left many issues unsettled. In particular, the evidence on the total gains to the takeover, i.e., the combined target and bidder returns, remained unresolved. This motivated the critique from Roll (1986) who argued that the evidence at the time of the Jensen & Ruback (1983) survey was consistent with the hubris hypothesis that takeovers created no synergistic increase in value and were merely manifestations of overconfident bidders who provided a wealth transfer to target shareholders. It was not until the publication of Bradley et al. (1988) that systematic evidence showed a significant and positive increase in the combined bidder and target returns. Expanding upon these findings, more recent studies have further defined the key drivers of shareholder value creation in acquisitions, including enhanced market power, greater innovation, achieving productivity improvements for acquirers and realizing synergies between acquirers and targets (David & Tertilt, 2021; Eckbo, 2014; Fathollahi et al., 2022; Hoberg & Philips, 2010). In a related study, Eckbo & Thorburn (2013) delve into corporate financial restructuring through M&A transactions, showing that these types of activities can effectively neutralize the downsides of over-diversification and thereby create significant shareholder value. They find that by reallocating assets more effectively, refining capital structures and bolstering managerial incentives, financial engineering can significantly elevate firm value. This indicates that the questions surrounding the "why" and "when" in M&A literature are critical, yet, the "how" aspect – pertaining to the structuring of these types of transactions and its impact on the investment outcomes – also holds significant importance. This is further underscored by Vladimirov (2015), who finds that bidder financing structures in the context of M&A transactions should be a first-order determinant in these types of corporate investments.

2.2 Financing structures in M&A

Generally, large corporate investments, like M&A, can be financed through various financial instruments: cash reserves, debt, equity or a mix of the former. Debt instruments encompass traditional bank loans, bond issuances and syndicated loans, while equity instruments primarily include stock issuances and private equity investments. Additionally, alternative financing sources like asset-backed financing, vendor financing, convertible securities or hybrid instruments are also viable financing options.

Myers & Majluf's (1984) Pecking-Order Theory posits a preference hierarchy for corporate investments where firms favor internal over external financing and debt over equity in security issuance due to tax considerations and information asymmetry. According to this theory, firms are inclined to utilize cash reserves for financing large corporate investments, converting to debt financing only when internal funds prove insufficient. Consistent with this theory, early evidence from Bruner (2004) suggests that cash is a predominant form of payment in M&A, especially in smaller acquisitions and during periods of stock market depression. However, contrasting evidence from Chen (2020) shows that equity-financed acquisitions can, under certain conditions, lead to more favorable outcomes, suggesting the presence of additional factors influencing financing decisions in M&A investments.

Martynova & Renneboog (2009) elaborate on these considerations showing that the financing decision of the bidding firm is explained by the Pecking-Order Theory, the acquirer's cost of capital and a bidder's preference for the method of payment. In line with the Pecking-Order Theory, internal funds are primarily used by cash-rich firms. When internal funds are insufficient, companies with low leverage prefer borrowing, while firms with high pre-takeover stock price run-ups favor equity issuance. Combining the payment method and the source of financing, Martynova & Renneboog (2009) show that strategic preferences for the payment method influence the underlying financing decision. If an acquirer seeks risk sharing and therefore prefers stock payment, equity financing is applied. However, if the acquirer is susceptible for control change, equity financing is less likely. Erel et al. (2015, 2017) contribute to this discussion by exploring how financially constrained firms are impacted by acquisitions and how cash holdings of firms can shape M&A activity. Their findings imply that cash reserves enable firms to make significant investments even in challenging economic conditions, yet also potentially lead to overinvestment in favorable economic climates. Uysal (2011) adds a layer to this analysis by linking the acquiring firm's capital structure with the frequency and nature of M&A transactions. His findings that firms with a "leverage deficit" undertake fewer deals illuminate the strategic adjustments companies make in anticipation of acquisitions. This interdependence between financing and investment decisions is critical for understanding M&A dynamics.

While utilizing internal cash reserves for financing transactions demonstrates benefits in terms of reduced cost of capital and enhanced financial flexibility, several studies imply that this approach may have its drawbacks. Sperling (2010) provides a critical analysis, suggesting that cash-rich firms may engage in value-destroying acquisitions due to potential agency problems between managers and owners. This perspective is further extended by Bruslerie (2013) who finds that financing acquisitions through internal funds could result in negative long-term results if managers are entrenched with empire building behavior. Contrary to the notion that cash payments result in lower acquisition premiums due to their inherent certainty and liquidity, Bruslerie (2013) finds that cash transactions often involve higher premiums and abnormal returns for target shareholders.

Bharadwaj & Shivdasani (2003) first examine under which circumstances bank financing is more likely to be used to fund large corporate investments. As expected, bank financing prevails when the acquirer’s cash reserve is low or the relative size of the takeover is large. Adding another dimension, Fischer (2017) suggests that utilizing credit facilities for takeovers can enhance both the selection of the target and the subsequent integration process. Banks, in this role, not only assist in the initial screening but also play a crucial part in monitoring the integration phase. Another strand of literature adds a layer to this discussion by departing from the traditional view that creditors have a passive monitoring role and only become active during default or bankruptcy. They highlight the importance of creditor governance prior the extreme distress as well, suggesting a more proactive involvement in corporate oversight (Chava & Roberts, 2008; Nini et al., 2012; Ozelge & Saunders, 2012).

Whereas debt-funded transactions have their advantages in terms of monitoring and tax deductibility, studies have shown adverse characteristics in these funding structures as well. First of all, these types of transactions coincide with periods of high market valuation (Dong et al., 2006; Rhodes-Kropf et al., 2005) and negative long-term returns (Agrawal et al., 1992;

Asquith, 1983; Loughran & Vijh, 1997; Rau & Vermaelen, 1998). This argument mainly relies on the theory of market-timing which is, among others, discussed in Baker & Wrugler (2002) stating that companies have an incentive to time the market and hence issue shares when prices are high and buy them back when prices are low. Still, acquisition finance can be driven by motives other than market-timing (i.e., paying with overvalued stock). Harford et al. (2009) and Uysal (2011) show that, when a bidder's leverage is higher than "optimal", it is less likely to finance a bid with debt than with equity. Other factors affecting acquisition finance include the taxation of cash and stock offers (Gilson et al., 1988) and risk sharing (Hansen, 1987). Whereas it is straightforward to understand why overvalued acquirers have an incentive to pay with stock, it is more ambiguous why targets would accept these offers. Explanations range from investor irrationality (Shleifer & Vishny, 2003) and correlation in valuation errors (Rhodes-Kropf & Viswanathan, 2004) to shareholder inertia (Baker et al., 2007) and governance problems in target firms (Hartzell et al., 2004).

Equity-financed transactions mostly involve considerations on market-timing and information signaling. Myers & Majluf's (1984) work suggests that the market interprets equity issues as a signal of overvalued company stock leading to negative market reactions following the announcement of the transaction. Managers may attempt to time the market, issuing equity during peak periods to capitalize on overvaluation. This strategy can be particularly pronounced in M&A financed entirely with equity, where the use of overvalued equity to acquire undervalued targets is seen as exploiting the mispricing premium (Rhodes-Kropf & Viswanathan, 2004; Shleifer & Vishny, 2003). Furthermore, the choice of equity payment in M&A can be perceived as a negative signal about the uncertainty of the target firm's quality and the potential for realizing synergies. This leads to sharing the risks associated with unrealized anticipated synergies between the acquirer's and the target's shareholders. Empirical studies, including those by Moeller et al. (2004), Andrade et al. (2001) and Martynova & Renneboog (2009), confirm the negative market reaction to equity-paid M&A. In addition to informational and market-timing concerns, Martynova & Renneboog (2009) argue that also a firms regulatory environment plays a role in shaping their corporate financing decisions. La Porta et al. (1997, 1998) and Djakov et al. (2007) underpin this argument by highlighting the impact of regulation on the terms of financing. Their work posits that strong corporate governance standards, in particular in cross-border acquisitions, can lead to lower costs of external finance due to their more protective characteristics.

2.3 Macroeconomic influences on M&A

Monetary and macroeconomic policies play a pivotal role in shaping the landscape of M&A transactions by influencing both the financing costs and the broader economic environment under which these transactions occur. Eckbo (2009) underscores the financial intensity and the dependance of M&A deals on fundamental economic conditions, which are in turn significantly impacted by monetary policy decisions. This perspective is further expanded by Galí & Gambetti (2015) and Summers (2014), who highlight the complex relationship between monetary policies and the economic environment within which M&A activities are situated.

Bernanke & Blinder (1992) and Jiménez et al. (2012) lay the foundation by illustrating how monetary policy directly affects financing costs, a topic further explored by Adra et al. (2020). They note that increases in federal funds rates can lead to negative market reactions to M&A announcements, substantial post-acquisition financing challenges and a higher likelihood of deal withdrawal. This connection between monetary conditions and the M&A landscape is supported by the findings of Campa & Hernando (2009) who observe that lower corporate bond spreads, indicative of the cost and availability of credit as influenced by monetary policy, are associated with reduced value creation in M&A transactions. This suggests that the cost and availability of credit, as influenced by monetary policy, are critical factors in determining the attractiveness and success of M&A deals.

The macroeconomic perspective is broadened by Kumar et al. (2023), who identify that, apart from interest rates, also inflation, real exchange rate and Gross Domestic Product (GDP) have a critical influence on M&A activity. All these factors, through their influence on the economic climate and the availability of credit, play a critical role in shaping M&A decisions. This view is supported by studies such as those by Tolentino (2010) and Vissa & Thenmozhi (2022), which link lower interest rates to increased M&A activity by reducing financing costs. In addition, inflation introduces a layer of complexity by affecting the cost of capital and the expected returns on investments (Boateng et al., 2015). High inflation rates are associated with a higher cost of debt and a higher propensity for deal withdrawal, reflecting the broader economic tensions and uncertainties stemming from fluctuating policy environments, as found by Uddin & Boateng (2011) and Todtenhaupt et al. (2020). GDP serves as a proxy for economic conditions and growth prospects, with a higher GDP indicating a favorable environment for M&A due to increased profits and funds for expansion (Choi & Jeon, 2011; Ibrahim & Raji, 2018; Sha et al., 2020). This suggests that macroeconomic stability and growth are conducive to M&A activities, facilitating strategic corporate expansions.

However, the macroeconomic environment also introduces uncertainties that can adversely affect M&A transactions. Hotchkiss et al. (2005) and Fu & Tang (2016) find that fluctuations in interest rates can complicate financing arrangements, affecting the cost of capital and potentially deterring M&A deals. In addition, policy-related uncertainties, such as uncertainties related to tax and to regulatory and monetary policies can hamper economic recovery and, by extension, M&A activities (Stock & Watson (2012), Julio & Yook (2012) and Gulen & Ion (2016). Nguyen & Phan (2017) specifically highlight the impact of government policy uncertainty on the M&A process. They find that uncertainty in areas such as taxation, government spending and regulatory and monetary policies not only decreases the number of acquisitions but also extends the time required to complete these deals. Interestingly, their research suggests that during periods of heightened uncertainty, firms may prefer stock-based financing and pay lower bid premiums, possibly due to a more selective investment approach focusing on only the most promising projects.

The strategic responses of firms to these uncertainties are illustrated by Garfinkel & Hankins (2011) and Haddad et al. (2016), who link merger waves and leveraged buyout waves to economic conditions and the aggregate risk premium. These studies suggest that firms may initiate mergers or acquisitions as a hedge against economic uncertainties, suggesting a deeper interplay between corporate strategy and macroeconomic conditions.

2.4 Covid-19

The recent Covid-19 pandemic, categorized as a "rare disaster" by Pagano et al. (2022), has underscored the critical influence of monetary and macroeconomic policies on M&A activity. This global crisis introduced great uncertainty into the economic landscape, significantly affecting the availability of capital and consequently, M&A transactions. Maksimovic et al. (2013) note that such disruptions can increase differences in access to capital, with strong implications for M&A dynamics. Akdogu et al. (2021) further amplify this point, observing that while broad economic downturns tend to suppress M&A activity, sector-specific shocks may cause waves of consolidation within those industries.

The narrative of M&A responses to economic shocks is enriched by historical precedents such as the Global Financial Crisis (GFC) of 2008-2009. Martynova & Renneboog (2009) highlight that crises typically dampen M&A activity due to escalating uncertainty, investor risk-aversion and constrained credit markets. Erel et al. (2015) specifically cite the liquidity crunch during the GFC, which severely limited financing options for acquisitions.

Yet, within these crises lie opportunities for strategic repositioning and consolidation. Beltratti & Paladino (2013) demonstrate that, despite tightened credit markets post-GFC, firms with robust financials pursued opportunistic acquisitions, targeting undervalued assets and weakened competitors.

The Covid-19 pandemic necessitated swift and decisive fiscal and monetary interventions to mitigate uncertainty and prevent a wave of corporate bankruptcies. Pagano et al. (2022) document an effective response of governments, financial markets and central banks in facilitating access to external funding for firms. Nonetheless, these interventions have dramatically transformed the investment landscape and liquidity conditions, with significant ramifications for M&A strategy, funding and execution. The post-pandemic period has been marked by escalating inflation, fueled in part by rising energy costs due to geopolitical tensions, notably the war in Ukraine. Inflation rates in the United States (US), for instance, surged to 7% in 2021 and 6.5% in 2022, far exceeding the Federal Reserve's target of around, but below 2%. In response, the Federal Reserve escalated its federal funds rate (FFR) from near-zero in 2020 to approximately 5.5% by 2023, signaling a dramatic shift in monetary policy.

These macroeconomic shifts are expected to lead to profound changes in M&A financing structures, which are inherently sensitive to economic fluctuations. Tightening credit markets, rising capital costs and evolving investor sentiment are expected to steer M&A financing towards more equity-based funding. Yet, no research has been conducted on the change in financing climate in a post-Covid era. As such, definitive conclusions about the impact of recent changes in the economic environment on M&A financing strategies remain elusive, underscoring the need for further investigation in this evolving field.

3. Hypotheses development

This study aims to examine how the financing composition of M&A deals has been impacted by the changing financing climate in the aftermath of Covid-19. Despite an abundance of literature on M&A and its financing mechanisms, there exists a notable gap in the research focusing on recent changes in the economic environment and their impact on the structure of M&A financing. This study tries to fill this gap by assessing whether (or the magnitude of) a reallocation among specific financing instruments such as cash, debt and equity has indeed occurred. Additionally, this thesis aims to explore the different impacts of these changes across various sectors.

In the aftermath of the Covid-19 pandemic, the global economic landscape has undergone unprecedented transformations, providing a unique opportunity to further investigate the dynamics of this change in financing climate on the financing structure of M&A transactions. Drawing on insights from Martynova & Renneboog (2009) and Erel et al. (2015), there is a well-founded expectation that the financing structure of M&A transactions are highly responsive to economic downturns and prevailing uncertainties. These periods coincide with a contraction in credit markets, compelling firms to reconsider and realign their financing strategies. Baker et al. (2015) further emphasize that such periods of uncertainty can significantly influence corporate policies. Specifically, the liquidity constraints and tighter credit conditions are likely to have pushed firms towards diversifying their financing sources. In light of these considerations, the first hypothesis is stated as follows:

H1: *The post-Covid financing climate for M&A shows a reduced reliance on traditional debt financing and an increased use of cash- and equity-based funding*

Pagano et al. (2022) document the varied impact of the Covid pandemic across different industries, a finding that resonates with the work of Huszagh et al. (1992) and Bäurle & Steiner (2015), who assert that industries react distinctively to macroeconomic shocks. This divergence suggests that innovative industries such as technology and healthcare may experience a larger shift towards equity-based funding, capitalizing on their high-growth trajectory and minimizing reliance on costly debt. Conversely, stable sectors such as manufacturing, utilities and food production are likely to exhibit smaller changes in financing structures due to their stable cash flows which better facilitates debt reliance. Bäurle & Steiner (2015) further support this notion by demonstrating that the manufacturing sector tends to have a minimal response to macroeconomic fluctuations, whereas sectors such as banking and insurance respond more strongly, in particular to interest rate changes, due to their stronger reliance on debt financing. Given these insights, the second hypotheses are stated as follows, please refer to Table 9 in Appendix A for industry classifications alongside their rationale.

H2a: *The shift in financing structures in M&A transactions among US listed firms differs across various sectors*

H2b: *The shift in financing structures in M&A transactions among US listed firms is more pronounced in unstable sectors compared to stable sectors*

The significance of this study lies in its contribution to bridging the identified gap in the existing literature, by providing a profound understanding of how M&A financing strategies have adapted to the rapid alterations in the macroeconomic environment post-Covid. Therefore, this study not only enriches the academic debate but also provides strong practical implications for financial analysts, executives and policymakers.

4. Data

4.1 Sample construction

To examine a potential disparity in financing structures between the pre- and post-Covid era, this paper studies data from publicly traded corporations in the US from the period 2013 – 2023. The rationale behind a prolonged timespan of the pre-Covid period is to choose a period long enough to come up with a large dataset, as increasing the sample size enhances the reliability of the study (Brown & Warner, 1985). Using the Covid-19 pandemic as a natural experiment to distinct two time periods, this study identifies the years 2013 – 2019 as the pre-Covid period and the years 2020 – 2023 as the Covid and post-Covid period (for simplicity considerations hereafter denoted as "post-Covid" period), thereby following the definition of the World Health Organization (WHO) who declared the Coronavirus outbreak as a Public Health Emergency of International Concern on January 30th, 2020 (Jasarevic et al., 2020). Luo et al. (2022) shed light on how studying significant global disturbances, including the Covid-19 pandemic, provides valuable opportunities to investigate the ramifications of such extensive disruptions on M&A dynamics thereby enriching our comprehension of corporate adaptability and strategic realignments in response to economic turbulence.

In line with Luo et al. (2022), this study utilizes Bureau van Dijk's (BvD) Orbis and integrated Orbis M&A (formerly Zephyr) databases to retrieve acquisition and company financial data from the period 2013 – 2023. These databases contain information on over 489 million companies across the globe, with a 20-year or longer history in each location (Moody's Analytics, 2024). The selection of these databases is informed by their capacity to offer extensive and insightful details on the MoP for each M&A transaction. Whereas other well-known databases only report the portion of the deal funded with either cash or equity, Orbis M&A also provides detailed information on the portion of the transaction that is debt-funded. Subsequently, macroeconomic data is retrieved from Eikon's Refinitiv Datastream (formerly Thomson Reuters). This database is highly regarded in the academic community as the most widely available international data source (Landis & Skouras, 2021). Lastly, The Chicago Board Options Exchanges' (CBOE) Volatility Index (VIX) is retrieved from Wharton Research Data Services (WRDS).

Acquisition data is selected based on the following criteria:

1. The announcement date is between January 1st, 2013 and December 31st, 2023
2. The deal status is “Completed” or “Completed assumed”
3. The deal type is “Merger”, “Acquisition”, “Institutional buy-out”, Management buy-out” or “Management buy-in” (Alperovych et al., 2021)
4. The acquired stake represents a majority interest
5. The minimum deal value is 1 million United States Dollar (USD)
6. The acquirer is incorporated in the US

These selection criteria result in a total of 14,281 transactions conducted by 12,917 unique acquiring firms. Due to the presence of missing or incorrect data (i.e., the aggregate proportions of each financing instrument within the funding structure falling below 0.95 or above 1.05) a total of 7,359 transactions were omitted. Furthermore, an additional 4,064 deals were excluded on account of the acquirer not being listed on a publicly traded stock exchange. Subsequently, transaction data was matched with macroeconomic indicators and financial information specific to each acquirer by the use of BvD ID numbers. The final sample comprises a total of 3,295 transactions.

A breakdown of the sample distribution is displayed in Table 1. Panel A describes the sample construction. Panel B delineates the industry specific distribution with “Banking, Insurance, Real Estate and Trading” (23.0%) and “Personal and Business Services” (21.7%) representing the largest portions of the sample, underscoring the prominence of financial, real estate and service-oriented transactions in the dataset. On the contrary, industries such as “Utilities” and “Recreation” constitute minor fragments, with 1.5% and 1.6% respectively, indicating a lower dominance of these sectors within the sample.

Panel C describes the distribution per year, highlighting that 2,086 transactions (63.3%) occurred in the pre-Covid period, while 1,209 transactions (36.7%) were recorded in the post-Covid era. The year 2021 emerges as the most active in terms of transaction volume. Furthermore and in line with Martynova & Renneboog (2009), it is observed that the majority of transactions were mainly cash-funded and that debt is the least prominent source of financing. One of the reasons Martynova & Renneboog (2009) provide for minimized debt usage is the prevention of debt overhang and the ability for high-growth firms to maintain financial flexibility post-acquisition. Another, less prevalent explanation could be that firms use their internal debt capacity to increase leverage pre-acquisition and subsequently utilize their cash position to fund the transaction. Consequently, while the financing method would be recorded as cash, it would be fundamentally, yet imperceptibly underpinned by debt. Notably, the median market capitalization of acquirers in 2023 significantly surpasses those of preceding years, with the average of 2013 – 2022 at 2,386 million USD versus 8,667 million USD in 2023. Similarly, the average deal value in the period 2013 – 2022 (162 million USD) is much lower compared to 2023 (600 million USD). Given that only 64 transactions are recorded in 2023, substantially less than in any other year, this could indicate incomplete data for 2023. This is a plausible scenario, considering that for some firms the fiscal year 2023 might not have ended or undergone auditing at the time of this analysis.

Panel D provides insights in the distribution of transactions by acquisition type. A Chi-square test is conducted to assess independence of the two variables. The outcome of the test yields a p-value of 0.000 leading to a rejection of the null-hypothesis stating independence between the two variables. Consequently, this reveals a statistically significant relationship between the geographic nature of the transaction (i.e., whether it is cross-border or domestic) and its industry relatedness (i.e., whether it is vertical or horizontal). Specifically, it can be concluded that domestic deals are more often horizontal (63.9%) in comparison to cross-border deals (51.2%).

Table 1: Overview of the sample

Panel A: Sample construction	N
Initial sample – transactions	14,281
Transactions with missing or incorrect data	7,359
Transactions by unlisted acquirers	4,064
Final sample – transaction	3,295

Panel D: Sample by acquisition type	Vertical	Horizontal
N		
Domestic	963	1,705
Cross-border	306	321

Panel B: Sample distribution by industry

	N	%	Cum.
Banking, Insurance, Real Estate, Trading	759	23.03	23.03
Business Equipment	306	9.29	32.32
Chemicals	56	1.70	34.02
Communication	70	2.12	36.14
Construction and Construction Materials	87	2.64	38.78
Fabricated Products and Machinery	153	4.64	43.42
Food Products	100	3.03	46.45
Healthcare, Medical Equipment, Pharmaceutical Products	235	7.13	53.58
Personal and Business Services	716	21.73	75.31
Petroleum and Natural Gas	118	3.58	78.89
Recreation	51	1.55	80.44
Retail	84	2.55	82.99
Transportation	74	2.25	85.24
Utilities	50	1.52	86.76
Wholesale	64	1.94	88.7
Other	372	11.29	100.00
Total	3,295	100.00	

Panel C: Sample distribution by year

	N	Median acquirer market cap	Median deal value	Total deal value	Debt (%)	Cash (%)	Equity (%)	Other (%)
2013	253	2,411.10	98.00	108,296.79	2.17	73.82	20.89	3.12
2014	328	1,851.80	117.54	208,590.10	1.74	73.65	22.00	2.61
2015	346	1,537.70	122.23	286,825.03	1.82	67.59	27.13	3.47
2016	281	2,268.81	116.26	204,710.93	1.52	71.92	24.52	2.05
2017	296	2,248.51	147.00	179,776.71	1.31	71.44	25.12	2.15
2018	278	2,340.33	272.50	395,483.35	1.86	73.82	23.10	1.21
2019	304	2,932.84	148.47	408,685.32	2.26	68.91	26.05	2.79
2020	285	3,438.26	172.00	326,605.11	1.91	64.84	30.83	2.39
2021	502	2,740.96	259.50	469,055.62	1.62	69.85	27.36	1.18
2022	358	2,086.67	168.68	431,879.60	1.17	65.95	30.44	2.47
2023	64	8,667.04	600.00	220,603.57	2.28	83.43	12.89	1.41
Total	3,295	2,409.31	156.00	3,240,512.13	1.73	70.27	25.73	2.27
Pre-	2,086	2,121.11	130.55	1,792,368.23	1.81	71.45	24.23	2.51
Post-	1,209	2,939.08	212.90	1,448,143.90	1.59	68.23	28.32	1.86

Note: this table provides a comprehensive breakdown of the final sample comprising 3,295 transactions over the years 2013 – 2023. The sample consists of publicly traded corporations in the US and industries represent Fama-French industry classifications based on SIC codes (Fama & French, 1997). Every industry with less than 50 observations is labeled as "Other", of which a detailed breakdown can be found in Table 10 of Appendix B. Panel A describes the sample construction, Panel B, C and D delineate the sample distribution by industry, year and acquisition type, respectively.

Pagano et al. (2022) highlight the unprecedented impact of the Covid-19 crisis on the global economy, introducing substantial market uncertainty and affecting the availability of capital. The initial response involved enhanced government spending aimed at minimizing economic repercussions and corporate bankruptcies. Post-2021, this was followed by a surge in the overall cost of living and an overheating economy, leading to rising inflation to which central banks responded by raising interest rates. Table 2 provides a comprehensive overview of these critical macroeconomic indicators, illustrating that the Compound Annual Growth Rate (CAGR) for all variables has indeed exhibited a considerably stronger expansion in the post-Covid period compared to the pre-Covid era.

Table 2: Development of macroeconomic indicators

	GS	CPI	FFR
2013	3,132.58	223.01	0.25
2014	3,168.61	236.77	0.25
2015	3,233.42	237.04	0.28
2016	3,303.03	239.98	0.53
2017	3,397.14	245.18	1.13
2018	3,590.38	251.36	2.02
2019	3,789.88	255.75	2.23
2020	3,994.76	259.13	0.52
2021	4,193.05	272.65	0.25
2022	4,446.84	292.01	1.86
2023	4,741.32	305.16	5.26
CAGR: 2013 – 2019	3.23%	2.31%	44.01%
CAGR: 2020 – 2023	5.88%	5.60%	116.27%

Note: this table provides an overview of the development of key macroeconomic indicators in the sample. Each figure denotes the mean value of the variable for the specified year. Government Spending (GS) represents the US Government Consumption and Investment Account (trillion USD), Consumer Price Index (CPI) is a measure for inflation and the Federal Funds Target Rate (FFR) is the target interest rate set by the Federal Reserve and serves as a benchmark for short-term interest rates in the US.

4.2 Defining variables

4.2.1 Dependent variable – portion of the transaction that is funded through debt

The dependent variable in this analysis is defined as the proportion of the transaction that is financed through debt, serving as a key indicator of the financing structures employed in M&A transactions. This variable is of paramount importance as it sheds light on the leverage strategy adopted by acquiring firms in financing their acquisitions (Martynova & Renneboog, 2009). Furthermore, it provides insights into how firms strategically change their financing structures in response to changing macroeconomic conditions including rising interest rates, government interventions and market uncertainties in the post-Covid era.

Much of the existing MoP literature differentiates primarily between cash- and stock-based transactions, overlooking debt as a funding source in M&A transactions (e.g., Dong et al., 2006; Rhodes-Kropf et al., 2005; Vermaelen & Xu, 2014). For example, Vermaelen & Xu (2014) develop a model predicting the method of payment in acquisitions, considering both pre-transaction and pro-forma capital structures. Although they emphasize the importance of leverage in optimizing these capital structures, their model only addresses the choice between cash and stock payments without predicting the utilization of debt as a source of funding. Conversely, Martynova & Renneboog (2009) develop a prediction model for the choice of acquisition finance, including debt as a source of financing. While this enriches basic cash- versus stock-based financing literature, they do not address the impact of macroeconomic disruptions on the choice of financing in M&A transactions. As such, by selecting debt as the dependent variable and in light of macroeconomic disruptions, this study enhances the exiting body of literature by exploring strategic adjustments firms make in their financing decisions in these turbulent times.

4.2.2 Independent variable – time dummy for the post-Covid period

The independent variable in this study is a time dummy which is set equal to 1 if the year in which the transaction takes place is 2020 or later i.e., if the transaction takes place in the post-Covid period. The inclusion of a time dummy in the regression is used to identify time differential effects i.e., to find out whether there is a distinction in financing structures between the pre- and post-Covid eras (Hill et al., 2018).

4.2.3 Control variables

In this study, the dependent variable – the financing structure of the M&A transaction – is influenced by multiple factors, extending beyond the primary independent variable of the post-Covid time period. To account for these additional influences, this study incorporates a set of control variables. This process helps to isolate the specific effect of the independent variable on the dependent variable by holding constant the potential influence of other variables (Hill et al., 2018). As a result, it reduces the likelihood of omitted variable bias, where the omission of relevant variables leads to inaccurate estimates of the relationship between the variables of interest. Additionally, Hill et al. (2018) describe that controlling for these other factors can improve the precision of the estimated coefficients, leading to more accurate and reliable conclusions about the relationships being studied. The set of control variables incorporated in this study can be classified as (A) firm-specific, (B) deal-specific, (C) macroeconomic or (D) industry-fixed. All continuous variables are winsorized at the 2.5% and 97.5% level of the distribution to mitigate the impact of outliers. This section is followed by a detailed description of the control variables alongside their expected influence on the dependent variable.

A. Firm-specific:

Following Nguyen & Phan (2017), the firm-specific control variables included in this study are *(i) Size, (ii) Profitability, (iii) Leverage, (iv) Leverage_c, (v) Liquidity, (vi) Growth options* and *(viii) Age*. Due to issues relating to missing data, control variables such as Capex intensity, R&D intensity and Dividend pay-out ratio are disregarded as control variables.

i. *Size:* the size of the acquiring firm is measured as the natural logarithm of its total assets. Vermaelen & Xu (2014) find that larger firms, having more resources and potentially better access to capital markets, prefer equity financing to maintain a more conservative capital structure post-acquisition. Therefore, we expect the relationship between the acquirer's size and the portion of debt funding to be negative (–).

ii. *Profitability:* ROA – measured as net income over the book value of assets – serves as an indicator of organizational profitability and represents one of the key elements of acquirers in M&A transactions (Liu & Giu, 2013). Consistent with Myers and Majluf's (1984) Pecking-Order Theory, we expect that more profitable firms are inclined to use retained earnings over external debt to finance large corporate investments and hence eliminate the drawbacks of external funding. As such, the relationship between profitability and debt financing is expected to be negative (–).

iii. *Leverage*: a firm's existing leverage, measured as displayed in Formula 1, is included to account for the overall capital structure and financial strategy of the acquiring firm. Firms with higher leverage ratios are likely to have higher debt capacity or tolerance due to better diversification of their assets, stronger growth opportunities or strategic approach to leverage debt for growth (Agliardi et al., 2016). Controversy, as firms have higher current leverage ratios, the ability to attract new debt might be limited if the firm (nearly) reaches its debt capacity (Modigliani & Miller, 1958). As such, we expect an inverse U-shape relationship between the level of existing leverage and debt financing in M&A.

$$\frac{ONCL + NCLI + CULI + OCLI}{TOAS} \tag{1}$$

iv. *Leverage_c*: represents the firm's change in leverage post-transaction compared to its pre-transaction leverage. This control variable is included to account for the possibility of firms to utilize their inherent debt capacity to raise funding prior to the transaction and to subsequently employ the liquidity obtained to fund their M&A transactions. Under this scenario, the transaction would be recorded as cash-funded, while the fundamental source of financing is debt. The relation between the change in leverage and portion of the transaction that is debt-funded is hence expected to be negative (–).

v. *Liquidity*: the acquiring firm's liquidity is proxied by its current ratio, defined as the ratio of its current assets divided by its current liabilities. It reflects a firm's ability to cover short-term obligations, which is indicative of its financial health and operational efficiency. Higher liquidity insinuates that the firm may have more internal funds at its disposal, potentially reducing the necessity to fund acquisitions through (more expensive) debt. This is evidenced by Yang et al. (2019) who find a positive relationship between corporate liquidity and cash-funded acquisitions. Following this reasoning, the relationship between the acquiring firm's liquidity and the portion of the transaction being debt-funded is expected to be negative (–).

vi. *Growth options:* the acquiring firm's growth opportunities are best proxied by its Tobin's Q, measured as the firm's market-to-book ratio (Adam & Goyal, 2008). This proxy reflects the market's expectations about a firm's growth potential, with higher levels of Tobin's Q potentially reflecting overvaluation of its stock. Martynova & Renneboog (2009) find that high-growth firms prioritize financial flexibility and want to prevent issues relating to debt overhang. Consequently, high-growth firms are more inclined to use equity- or cash-based financing to fund transactions. As such, the relationship between a firm's growth opportunities and the amount of the transaction being funded by debt is expected to be negative (–).

vii. *Age*: the acquiring firm's age is constructed as the year in which the transaction took place minus the year in which it was incorporated and serves as an indicator of the firm's stability. Evans (1987) finds that older firms are more stable and have lower probability of failure, which are important determinants of its capacity to raise debt to fund transactions. As such, the relationship between a firm's age and the amount of debt used to fund a transaction is expected to be positive (+).

B. Deal-specific:

Following Martynova & Renneboog (2009), the deal-specific control variables included in this study are *(i) Deal value, (ii) Cross-border, (iii) Target listed* and *(iv) Horizontal*. Control variables such as the deal attitude (hostile versus friendly) are excluded due to data limitations.

i. *Deal value*: the deal value is measured as the natural logarithm of the value of the deal which is measured in million USD. This transformation is done to normalize the distribution of deal values and to remove the impact of outliers. Controlling for deal size allows the analysis to account for inherent variations in funding structure across different sizes of deals. Large corporate takeovers generally come with higher risks. Since acquirers have a desire to share the risks associated with these large takeovers, they have a higher propensity to fund these transactions using stock (Martynova & Renneboog, 2009). As such, the expected correlation between the deal size and the portion of debt used to fund the transaction is negative (–).

ii. *Cross-border*: represents a dummy variable that is set equal to 1 if the target is not incorporated in the US and is set equal to 0 if both the acquirer and the target are incorporated in the US, the transaction is then classified as domestic. Martynova & Renneboog (2009) find that cross-border deals often face unique challenges, one of which includes the target firms' hesitance towards accepting stock offers, particularly when the acquiring entity is not listed on a stock exchange within the target's country. Consequently, they find that cross-border deals have a lower likelihood of being financed through equity. Following this reasoning, the relationship between the portion of the deal being debt-funded and the deal being cross-border is expected to be positive (+).

iii. *Target listed:* indicates a dummy variable that is set equal to 1 if the target is listed on a publicly traded stock exchange i.e., the target is public. Alternatively, the dummy variable is set to 0 and the target is classified as private. Given strong scrutiny of analysts and investors, acquiring firms are less likely to use intense debt in financing their transactions to avoid overleveraging and adverse market reactions (Uysal, 2011). The need to safeguard a prudent capital structure and maintain credit ratings may then lead to a preference for equity-based funding. As such, we expect the relations between a publicly listed target and the amount of debt used to fund a transaction to be negative (–).

iv. *Horizontal*: denotes a dummy variable that is set equal to 1 if the acquirer's and the target's industry are equal i.e., the transaction type is classified as horizontal.

Alternatively, the dummy variable is set to 0 and the transaction is classified as vertical (otherwise known as diversifying), thereby serving as an indicator for the industry relatedness of the transaction. Diversification can influence funding structure due to perceived risk and strategic alignment (Feito-Ruiz & Menéndez-Requejo, 2012). The authors find that in well-regulated markets, vertical transactions might be scrutinized for potential agency issues, leading to a preference for stock or cash financing. As such, the expected relationship between debt funding and deal diversification is negative (–).

C. Macroeconomic:

Following Adra et al. (2020) and Kumar et al (2023) the macroeconomic control variables included in this study are *(i) S&P500_r, (ii) CCI_c* and *(iii) GDP_g*. The Real Effective Exchange Rate (REER) is excluded due to the fact that this study only encompasses one country with a dominant and stable currency (USD).

i. *S&P500_r*: the return on the Standard and Poor's 500 (S&P500) index is included to account for a measure of business cycle and stock market performance (Martin, 1996). Martin (1996) finds that the state of the economy significantly influences financing choices in M&A transactions . In addition, Vermaelen & Xu (2014) find that high stock market performance, with potentially overvalued equity, reduces firms' propensity to pay with stock in order not to dilute shareholders' value with overvalued equity. This implies stronger reliance on (among others) debt funding in M&A transactions. Hence, the relationship between debt financing and stock market performance is expected to be positive (+).

ii. *CCI_c*: in line with Nguyen & Phan (2017) the year-on-year (y-o-y) change in the Consumer Confidence Index (CCI) is included as a control variable to proxy overall consumer sentiment with a potential impact on the broader economic environment in which M&A transactions take place. Higher consumer confidence is likely to enhance economic growth and investment levels which, through their effect on the availability of credit, are likely to increase the feasibility of debt funding in large corporate investments. As such, the expected relationship between CCI and the level of debt funding in M&A is expected to be positive (+).

iii. *GDP_g*: the level of GDP growth serves as a measure of aggregate economic conditions (Adra et al., 2020). Strong economic conditions may boost firms' and lenders' confidence which may increase the level of debt used to fund large corporate investments (Kumar et al., 2023). Following this reasoning, we expect the relationship between the level of debt financing in a transaction to be positively (+) related to the level of economic growth.

D. Industry-fixed

This study includes industry-fixed effects as a control variable to account for specific industry characteristics. Industries differ in their capital structures, regulatory environments and market dynamics, all of which can impact the availability, cost and attractiveness of debt financing in M&A transactions (Schmalensee, 1985). Industries are categorized using Fama-French industry classification based on Standard Industrial Classification (SIC) codes (Fama & French, 1997). Every industry with less than 50 observations is labeled as "Other", of which a detailed breakdown can be found in Table 10 of Appendix B.

4.3 Descriptive statistics

In order to assess if a shift among financing instruments has occurred in the post-Covid time period, this study employs the proportion of an M&A transaction that is financed through debt as the dependent variable. After analyzing the dependent, independent and control variables for overall plausibility (i.e., studying their distribution, extreme values and linearity), all continuous variables are winsorized at the 2.5% and 97.5% level of the distribution. Table 3, Panel A displays the summary statistics for all variables included in this study. It should be noted that *Size* – as proxied by the acquirer's total assets – and *Deal value* are transformed by taking their natural logarithms to minimize the effect of outliers and make the interpretation of their coefficients more comprehensible.

Notably, the mean proportion of debt used to fund transactions is quite low at 1.7%, with a majority of transactions (70.3%) primarily funded with cash. This is in line with Martynova & Renneboog (2009) and highlights a predominance of cash financing in M&A transactions. The equity component is also significant at a mean of 25.7%, although the high standard deviation indicates strong variability in its use across transactions. A plausible explanation for the high cash component could stem from the fact that firms use their inherent debt capacity to raise debt pre-transaction and use the obtained liquidity to fund their transactions with cash payments. Such a transaction would be recorded as cash-paid, while the fundamental funding stems from debt financing. Consequently, firms' leverage ratio (*Leverage)* and its pre-transaction change in leverage (*Leverage_c)* are observed to assess if such an increase in leverage indeed occurs. From Table 3, Panel B it can be observed that the mean change in leverage is higher for acquirers who use debt in their financing structure (13.3%) versus acquirers who do not employ debt financing (5.7%). A t-test for mean difference yields a p-value of 0.003. This finding supports the prior argumentation that acquirers predisposed to utilizing debt financing (denoted by dDebt = 1) may indeed increase their leverage pre-transaction. The liquidity raised could subsequently be employed to fund the transaction in cash.

Firm-specific control variables such as *Size, Profitability, Leverage, Leverage_c, Liquidity, Growth options* and *Age* offer insights into the financial health and strategic positioning of the acquiring firms, with *Size* and *Leverage* standing out because of their relatively high means, indicating that larger and highly leveraged firms are more actively engaging in M&A. Although the variability in *Age* is quite significant, maturity of all acquirers in the sample can be assumed given the fact that these companies are listed on a stock exchange.

Macroeconomic indicators such as the *S&P500_r*, *CCI_c*, *GDP_g*, *VIX*, *CPI_c* and *Fund rate* are included to control for broader market conditions and economic effects. Relatively large variation in the distribution of these variables indicate fluctuating market sentiments which resonates with the time period under investigation in this study.

Table 11 in Appendix C provides an overview of the summary statistics, delineating the dataset into the pre- and post-Covid period. Notably, there is a slight decrease in the mean proportion of cash financing from 71.4% in the pre-Covid period to 68.2% in the post-Covid period, proposing a potential shift in financing preferences after the pandemic. The mean proportion of debt financing in M&A transactions has experienced a slight decrease from 1.8% pre-Covid to 1.6% post-Covid. Furthermore, significantly higher mean values of *VIX*, inflation (*CPI_c*) and interest rate (*Fund rate*) are observed in the post-Covid period in line with observations mentioned earlier in this study.

Table 3: Summary of regression statistics

Panel A: Full sample						
	N	Mean	SD	Min	Median	Max
Debt	3,295	0.017	0.100	0.000	0.000	1.000
Cash	3,295	0.703	0.402	0.000	1.000	1.046
Equity	3,295	0.257	0.389	0.000	0.000	1.025
Other	3,295	0.023	0.108	0.000	0.000	1.000
Covid	3,295	0.367	0.482	0.000	0.000	1.000
Total assets	3,295	18,859.386	78,634.440	0.065	2,894.200	2,415,690.000
Size	3,295	7.766	2.243	0.063	7.971	14.697
Profitability	3,295	-0.596	14.251	-54.946	2.243	17.564
Leverage	3,295	0.788	0.288	0.193	0.770	1.556
Leverage_c	3,295	0.061	0.318	-0.584	0.012	1.352
Liquidity	3,295	2.215	1.804	0.409	1.721	9.568
Growth options	3,295	1.386	1.334	0.098	1.002	6.189
Age	3,295	26.402	25.812	0.000	19.000	112.000
Dealvalue_o	3,295	983.463	4163.819	1.000	156.000	108,700.000
Deal value	3,295	11.949	1.946	6.908	11.958	18.504
Cross-border	3,295	0.190	0.393	0.000	0.000	1.000
Target listed	3,295	1.007	0.081	0.000	0.000	1.000
Horizontal	3,295	0.615	0.487	0.000	1.000	1.000
S&P500_r	3,295	13.495	12.963	-19.953	13.801	62.715
CCI_c	3,295	7.396	17.194	-35.693	8.355	39.697
GDP_g	3,295	2.529	1.925	-2.213	2.467	5.800
VIX	3,295	18.036	6.422	10.125	16.722	57.737
CPI_c	3,295	2.811	2.448	-0.200	1.940	9.060
Fund rate	3,295	0.983	1.109	0.250	0.250	5.500
Panel B: By dDebt						
dDebt = 0	N	Mean	SD	Min	Median	Max
Leverage	3,134	0.787	0.284	0.193	0.770	1.556
Leverage_c	3,134	0.057	0.309	-0.584	0.012	1.352
dDebt =1						
Leverage	161	0.793	0.351	0.193	0.774	1.556
Leverage_c	161	0.133	0.451	-0.584	0.025	1.352

Note: this table provides a comprehensive overview of the regression statistics. Debt, Cash, Equity and Other represent the portions of the transaction funded with the respective instruments. Covid is a dummy variable equal to 1 if the transaction takes place in the post-Covid period. Size is a firm-specific control variable measured by the natural logarithm of Total Assets (million USD). Profitability, Leverage, Leverage_c, Liquidity, Growth options and Age are all company-specific control variables displayed in their natural form. Deal value is a deal-specific control variable calculated as the natural logarithm of Dealvalue_o (million USD). Cross-border, Target listed and Horizontal are all dummy variables equal to 1 if the deal is characterized as cross-border, public target or horizontal, respectively. S&P500_r, CCI_c, GDP_g and CPI_c represent the y-o-y increase of the S&P500 Index, CCI, GDP and CPI, respectively. VIX is the CBOE's Volatility Index. Fund rate is the Federal Reserves' target interest rate in percentages. dDebt is a dummy variable set to 1 if the transaction involves debt financing.

5. Methodology

5.1 Regressions

In order to analyze whether a shift in financing structures in M&A transactions in the post-Covid time period has indeed occurred, this study employs Stata's linear regression analysis. Linear regression analysis is a statistical method used to model the relationship between a dependent variable and one or more independent variables (Davidson & MacKinnon, 1993). Stata estimates the coefficients of the linear regression model using the Ordinary Least Squares (OLS) method. OLS minimizes the sum of squared differences between the observed values and the values predicted by the linear model (StataCorp, 2023; Davidson & MacKinnon, 1993). According to the Gauss-Markov Theorem, we need the estimators of the coefficients in the linear regression model to be Best Linear Unbiased Estimators (BLUE) in order for the OLS model to be valid. The underlying assumptions include no perfect multicollinearity, zero conditional mean of errors and homoskedasticity. These underlying assumptions will be tested in Section 5.2 of this paper.

To evaluate the first hypothesis:

H1: *The post-Covid financing climate for M&A shows a reduced reliance on traditional debt financing and an increased use of cash- and equity-based funding*

the following regression model is employed:

$$debt_i = \beta_0 + \beta_1 dCovid_i + \theta Controls_i + \psi Industry_i + \varepsilon_i \tag{2}$$

where *i* represents the unique deal announced and $debt_i$ is the portion of that unique transaction that is financed through debt. The variable $dCovid_i$ is a dummy equal to 1 if the transaction takes place during the period 2020 – 2023 and 0 if the transaction occurred in the period 2013 – 2019. $Controls_i$ is a vector of firm-specific, deal-specific and macroeconomic control variables, the inclusion of which is explained in Section 4.2 of this paper. The variable $Industry_i$ is included to account for industry-fixed effects and lastly, ε_i represents the error-term. In line with the first Hypothesis, a statistically significant negative β_1 coefficient implies that the post-pandemic period is characterized by a reduced reliance on traditional debt. Conversely, a positive and statistically significant coefficient would imply that firms employed more debt financing in their M&A investments in the post-Covid period. As such, the β_1

coefficient provides insights into how the post-Covid period might have influenced debt financing in M&A transactions.

In order to evaluate the second hypotheses:

H2a: *The shift in financing structures in M&A transactions among US listed firms differs across various sectors*

H2b: *The shift in financing structures in M&A transactions among US listed firms is more pronounced in unstable sectors compared to stable sectors*

two regressions are performed. First, it is assessed if the post-Covid effect is heterogenous across sectors, using the "Healthcare, Medical Equipment and Pharmaceutical Products" sector as the baseline industry. For evaluation, the following regression model is employed:

$$debt_i = \beta_0 + \beta_1(dCovid_i * Industry_i) + \theta Controls_i + \psi Industry_i + \varepsilon_i \qquad (3)$$

where the interaction term $\beta_1(dCovid_i * Industry_i)$ allows for an assessment of a differential effect of the post-Covid era on debt financing over sectors. A positive and statistically significant β_1 coefficient indicates that the impact of the post-Covid period on debt levels in M&A financing is more pronounced in certain industries than in others in comparison to the baseline industry. A negative and statistically significant coefficient implies a less pronounced effect of the post-Covid period on debt levels in certain industries compared to the baseline industry.

The second regression model employed is specified as follows:

$$debt_i = \beta_0 + \beta_1(dCovid_i * IndustryClass_i) + \theta Controls_i + \psi Industry_i + \varepsilon_i \qquad (4)$$

where $IndustryClass_i$ is a dummy variable set equal to 1 if the industry is classified as unstable. This regression allows for testing if the post-Covid period effect on debt financing in M&A transactions is more pronounced in unstable versus stable sectors.

5.2 Data and model testing

5.2.1 Stationarity

It is well-established in economic literature that macroeconomic data often exhibit non-stationarity (Nelson & Plosser, 1982). Non-stationarity occurs when, for example, the means and variances of variables change over time. A non-stationary variable can be defined as an exploding variable and can be unpredictable in regression analysis. As such, it can lead to misleading results, by showing a relationship that does not exists (Hill et al., 2018). In order to test for non-stationarity of the macroeconomic variables, an Augmented Dickey-Fuller (ADF) test is employed to identify a unit root in the variables. In this test, the null-hypothesis states that the variable contains a unit root and hence is non-stationary. The test statistics and corresponding p-values can be found in Appendix C (Table 12). Based on these test statistics, it is determined that *GDP, S&P500, CCI, CPI* and *Fund rate* all exhibit characteristics consistent with the presence of a unit root. Conversely, for the *VIX*, the null-hypothesis can be rejected, classifying this variable as stationary.

To cope with non-stationarity issues in the *GDP, S&P500, CCI* and *CPI* variables, y-o-y changes in these variables are computed. These modifications, which may alternatively be referred to as returns or growth rates, are intended to transform the original series into a stationary format suitable for further analysis. After performing another ADF test on these variables, it can be concluded that *GDP_g, S&P500_r* and *CCI_c* no longer exhibit a unit root. Consequently, these variables are now deemed suitable to incorporate as macroeconomic control variables in the regression analysis.

After generating the variable denoted as *CPI_c*, which represents the inflation rate, the outcome from the ADF test persistently suggest the presence of a unit root within this variable. Consequently, this variable has been omitted from inclusion as a control variable within the current model. Furthermore, the variable *Fund rate* has also been excluded from serving as a control variable. This decision stems from the rationale that computing its y-o-y change is deemed inapplicable and the original *Fund rate* variable exhibits a unit root.

5.2.2 Multicollinearity

Multicollinearity arises when one predictor variable in the OLS regression is highly correlated with another predictor variable. A high correlation between two of the predictor variables can make it difficult to determine the individual effect of each individual predictor on the dependent variable. As a result, the coefficients may not be reliable or exhibit large variances. In addition, multicollinearity can affect the statistical significance of independent variables, causing their significance to appear lower than it truly is (Hill et al., 2018). Consequently, it is paramount to check for multicollinearity between independent variables in regression analyses (Daoud, 2018).

The presence of multicollinearity in this model is assessed using Variance Inflation Factors (VIFs) and Pearson correlation coefficients. VIFs measure how much the variance of an estimated coefficient increases because of collinearity with values exceeding 10 indicating strong collinearity (Belsley et al., 1980; Kyriazos & Poga, 2023). While cutoff levels for assessing multicollinearity using Pearson correlation coefficients in the literature vary, a common benchmark is 0.7 (Kumar et al., 2023). The results of the analyses can be found in Table 13 and Table 14 of Appendix C. Based on both methods, the presence of multicollinearity within the dataset employed is not detected.

5.2.3 Heteroskedasticity

Heteroskedasticity, defined as the non-constant variance of error terms, can lead to inefficient estimations and inaccurate standard errors, affecting the reliability of hypothesis testing in OLS regression analysis (Hill et al., 2018). As such, testing the dataset for presence of heteroskedasticity is important to improve the model's estimation accuracy and the validity of its inferential results. In order to assess whether the data employed in this model exhibit heteroskedasticity, a Breusch-Pagan test is employed. The null-hypothesis in this test posits that the variance of the errors is constant (i.e., homoskedasticity). Based on the findings of the Breusch-Pagan test, yielding a p-value of 0.000, the null-hypothesis is rejected, thereby indicating the presence of heteroskedasticity within the dataset.

The presence of heteroskedasticity indicates that the residuals do not adhere to a normal distribution. This deviates from the assumption of homoskedasticity fundamental to OLS regression analysis (Hill et al., 2018). To address this, this study uses robust standard errors in the regression analysis. In addition, logistic and Tobit regression analyses are employed in the robustness section, as these methods have different underlying assumptions compared to OLS regression. This approach is utilized to ascertain the consistency of the findings despite the heteroskedastic nature of the dataset. A detailed explanation can be found in Section 6.3.

5.2.4 Endogeneity

One of the foundational assumptions to OLS regression analysis is that the explanatory variables are uncorrelated with the error term i.e., there should be no relationship or correlation between the independent variables and the error term in the regression model (Hill et al., 2021). A violation of this assumption leads to biased and inconsistent estimates of the regression coefficients, making it difficult to accurately infer the effect of the independent variable on the dependent variable.

Endogeneity issues in regression analyses can arise due to various reasons, including measurement error, omitted variable bias and simultaneous causality (Roberts & Whited, 2013). In the context of this study, using financing structure as the dependent variable and the post-Covid time period as the independent variable, endogeneity poses a potential challenge. For example, neglecting to account for rising interest rates can conflate the effects of the post-Covid period with those of higher interest rates on the reduced usage of debt in M&A financing leading to omitted variable bias. Similarly, simultaneous causality presents an issue when enhanced market volatility post-Covid influences firms to leverage less debt in M&A financing. Concurrently, this shift towards less debt financing in response to the post-Covid environment could itself influence broader market and firm behaviors, creating a feedback loop that obscures the causal direction between the post-Covid landscape and M&A financing structures. Lastly, endogeneity might arise if only specific firms decide to engage in M&A, potentially due to their strong cash positions leading to a selection bias in the sample.

To test for the endogeneity of the independent variable in this study, a Hausman (1978) specification test, adapted for Instrumental Variable (IV) regression contexts, is performed. The results yield a Chi-squared statistic of 11.370 with a corresponding p-value of 0.001. This outcome leads to the rejection of the null-hypothesis, which posits that the independent variable can be treated as exogenous. Therefore, the analysis confirms the presence of endogeneity within the model. To mitigate this issue, the study employs a Two-Stage Least Squares (2SLS) IV approach, enhancing the accuracy of the model's predictions by properly accounting for the endogenous nature of the independent variable. A detailed outline of the IV estimation alongside its results can be found in Section 6 of this paper.

6. Empirical results

This section presents the empirical results derived from performing the regression analyses discussed in Section 5.1. To check the robustness of the results, this study complements the original OLS regression with a 2SLS IV regression, logistic regression and Tobit regression. Finally, a sensitivity analysis is employed to further validate the robustness of the results.

6.1 M&A financing in the post-Covid era

6.1.1 OLS regression analysis

Table 4 presents the OLS regression results examining the relationship between the financing structure of an M&A transaction and the post-Covid period. The first Column presents the results of the OLS regression as dissected in Formula 2. The regression coefficient for the independent variable, the post-Covid time dummy, is equal to -0.001. This indicates a negative relationship between the amount of debt financing and the post-Covid time period. Specifically, this coefficient indicates that, on average, the proportion of the M&A transaction that is financed through debt is 0.12 percentage points (p.p.) lower in the post-Covid period compared to the pre-Covid period. This relatively small change suggests that the shift to reduced debt reliance is not substantial. This is also reflected in the corresponding p-value of 0.777, indicating that the relationship between debt financing and the post-Covid time period is not statistically significant. As such, it cannot confidently be concluded that there is indeed a reduced reliance on debt financing in the post-Covid investment climate based on the OLS model.

It can be observed that the Adjusted R-squared for the first regression model is relatively low at 4.2%, which means that only 4.2% of the variability in the proportion of debt financing is explained by the variables included in the model. This can stem from statistical errors such as omitted variable bias or measurement error (Hill et al., 2018). Specifically, in this study this could stem from the imbalanced nature of the dataset employed, with a large number of transactions employing little to no debt financing. Alternatively, this may originate from more practical reasons such as the fact that the inherent complexity of debt financing including its strategic considerations, regulatory environments, firm-specific characteristics and market conditions may not be easily captured in a model. By performing similar regressions on cash- and equity-based funding, the applicability and depth of this study is enhanced. The explanatory powers of the cash and equity models are considerably higher at an Adjusted R-squared of 36.1% and 37.8%, respectively. Incorporating models for cash and equity financing serves to validate the findings derived from the debt financing model. The general consistency observed in statistical significance levels across all three models enhances the reliability of the study. Specifically, the absence of statistically significant coefficients of the independent variable in the cash and equity model support the conclusion of the debt model. This outcome indicates that it cannot confidently be concluded that a transformation in financing structures during the post-Covid era in comparison to the period preceding the pandemic has indeed occurred when considering an OLS regression model.

The absence of a shift in financing strategies in response to alterations in the macroeconomic climate present in the post-Covid period might have several underlying factors. First of all, firms may possess inherent resilience and stability in their financing strategies, enabling them to weather macroeconomic shocks without making significant changes to their capital structures. In addition, maintained financing strategies in times of economic turbulence might indicate swift monetary and fiscal responses from federal governments, central banks and financial institutions to maintain sufficient access to capital even in volatile economic conditions. This swift response and reliance on these institutions is also underscored by Pagano et al. (2022). Finally, the maintained financing strategies in the overall sample might differ from financing strategies in specific industries. Pagano et al. (2022) have previously documented that various sectors responded differently to the pandemic, depending on their resilience to social distancing, financial flexibility and corporate culture. The analysis in Section 6.2 will reveal if the aggregate analysis masks sector-specific trends where certain sectors have altered their financing strategies, while others have persisted their original structures.

When looking at the control variables, it can be observed that *Size, Leverage, Growth options, Deal value, Cross-border* and *Target listed* all have statistically significant coefficients at the 10% confidence level, indicating a meaningful relationship between the respective variables and the usage of debt in M&A financing. Specifically, the statistically negative coefficient for *Size* (-0.005) indicates that larger firms use less debt-funding for their M&A investments. These findings are in line with Vladimirov (2015) who also documents a negative relationship between acquirer size and debt-financing employed. The positive coefficient for *Leverage* (0.024) indicates that firms with higher current leverage ratios use more debt to finance their M&A, potentially due to higher debt capacity or risk tolerance. The negative coefficient for *Growth options* (-0.006) implies that firms experiencing high growth tend to use less debt to fund M&A transactions. This is in line with research from Vermaelen & Xu (2014) and corresponds with argumentation provided by Myers & Majluf (1984), suggesting that high-growth firms are less inclined to attract debt financing to maintain financial flexibility and minimize the costs of financial distress. The negative coefficient for *Deal value* (-0.002) suggests that larger deals utilize less debt funding in their M&A investments. The positive (0.011) and negative (-0.018) coefficients for the dummy variables *Cross-border* and *Target listed*, respectively, suggest that cross-border deals are associated with higher levels of debt financing, whereas acquisitions of public targets tend to rely less on debt financing.

Table 4: OLS regression results Formula 2			
	(1) Debt	(2) Cash	(3) Equity
Covid	-0.001	-0.007	0.016
	(0.004)	(0.014)	(0.013)
Size	-0.005***	0.060***	-0.053***
	(0.001)	(0.005)	(0.004)
Profitability	-0.000	0.008***	-0.008***
	(0.000)	(0.001)	(0.001)
Leverage	0.024**	0.114***	-0.152***
	(0.011)	(0.026)	(0.025)
Leverage_c	0.011	0.096***	-0.110***
	(0.010)	(0.021)	(0.021)
Liquidity	0.001	0.001	-0.000
	(0.001)	(0.004)	(0.004)
Growth options	-0.006***	0.017***	-0.010**
	(0.001)	(0.005)	(0.004)
Age	0.000	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Deal value	-0.002*	-0.051***	0.046***
	(0.001)	(0.005)	(0.004)
Cross-border	0.011*	0.007	-0.020
	(0.006)	(0.014)	(0.013)
Target listed	-0.018**	-0.063	0.106
	(0.008)	(0.081)	(0.083)
Horizontal	-0.007	-0.054***	0.057***
	(0.004)	(0.012)	(0.012)
S&P500_r	0.000	0.000	-0.000
	(0.000)	(0.001)	(0.006)
CCI_c	0.000	0.001	-0.000
	(0.000)	(0.000)	(0.000)
GDP_g	0.000	0.003	-0.002
	(0.001)	(0.004)	(0.003)
Industry FE	Controlled	Controlled	Controlled
Constant	0.122***	0.837***	0.0670
	(0.019)	(0.094)	(0.095)
Observations	3,295	3,295	3,295
Adj. R-squared	0.042	0.361	0.378

Note: this table provides the results of the OLS regression analysis with robust standard errors of the effect of the post-Covid time period on the funding structure of M&A transactions. Column 1 regresses the independent and control variables on the proportion of debt employed, whereas Column 2 and 3 perform regressions on the proportion of cash and equity employed. Covid represents a dummy variable equal to 1 if the transaction takes place in the post-Covid period. The post-Covid period comprises the years 2020 – 2023, while the pre-Covid period consists of the years 2013 – 2019. The regressions control for industry-fixed effects. Robust standard errors are displayed in parentheses. Significance levels are denoted as * for 10%, ** for 5% and *** for 1%.

6.1.2 2SLS regression analysis

One fundamental assumption of OLS regression is that the explanatory variables are independent of the error term, indicating that there should be no correlation between them (Hill et al., 2021). Violating this assumption leads to skewed and inconsistent coefficient estimations, which hinders the proper determination of the independent variable's effect on the dependent variable. Endogeneity in regressions can result from measurement error, omitted variables or simultaneous causality (Roberts & Whited, 2013). To assess the independent variable's endogeneity in this study a Hausman (1978) specification test tailored for IV regression is applied. The results yield a Chi-squared statistic of 11.370 and a corresponding p-value of 0.001, leading to a rejection of the null-hypothesis that the independent variable is exogenous, confirming endogeneity within the model. As such, in order to base solid conclusions regarding the first Hypothesis a 2SLS IV regression analysis is performed to deal with endogeneity present within the original OLS model.

The core assumptions that define a solid IV are (1) relevance and (2) exogeneity, i.e., the instrument should be strongly correlated with the endogenous variable (relevant) and have no direct relationship with the dependent variable or the error term in the regression, other than through its correlation with the endogenous variable (exogenous) (Newhouse & McClellan, 1998). The IVs included in this 2SLS regression analysis are *(i) VIX, (ii) CPI_p* and *(iii) Fund rate*.

i. *VIX*: CBOE's VIX is a widely used measure to account for financial market volatility. Since the post-Covid period is characterized by enhanced volatility which likely influences firms' financing strategies, VIX can be treated as a relevant measure for the post-Covid time period. In addition, VIX can be treated as exogenous since it is determined by market-wide expectations, factors external to individual firms' financing preferences.
ii. *CPI_c*: the y-o-y monthly percentage change in the US's CPI is used as a measure of the country's inflation rate. It can be treated as a relevant instrument for the post-Covid time period since this period was characterized by significant economic changes, including policy responses which can influence the cost of capital and hence M&A strategies. Furthermore, the inflation rate can be treated as exogenous as it is subjective to a broad set of macroeconomic factors, external to firm specific operations.
iii. *Fund rate*: the Federal Reserve's target interest rate is commonly used as a proxy for a countries' short-term interest rate. The changes in the macroeconomic climate characterized in the post-Covid time period can directly influence firms' cost of capital,

making it a relevant instrument. Additionally, the instrument can be treated as exogenous as it is set by the Federal Reserve and is not influenced by firm-specific actions.

In the first stage, the endogenous independent variable, which in this study refers to the post-Covid time dummy variable, is regressed on the instrumental variables alongside all control variables employed within the OLS regression model. As such, the formula for the first stage regression is as follows:

$$dCovid_i = \alpha_0 + \alpha_1 VIX_i + \alpha_2 CPI\_p_i + \alpha_3 FFR_i + \theta Controls_i + \psi Industry_i + \varepsilon_i \quad (5)$$

In the second stage, the original OLS regression model is performed again. Only now the original Covid time dummy variable is replaced with its predicted values obtained from the first stage regression, thereby cleaning the endogenous variable of its endogeneity by using the component that is not correlated with the error term in the original model (Newhouse & McClellan, 1998). Consequently, the formula for the second stage regression is as follows:

$$debt_i = \beta_0 + \beta_1 d\widehat{Covid}_i + \theta Controls_i + \psi Industry_i + \varepsilon_i \quad (6)$$

where $d\widehat{Covid}_i$ is the predicted value of $dCovid_i$ from the first stage regression.

In order to assess the validity of the instruments, three key tests are employed. The first test is the a Kleibergen-Paap *rk* Lagrange Multiplier test, which is performed to test for underidentification, with the null-hypothesis stating underidentification. The results are dissected in Table 5. The Chi-squared statistic of 1,092.814 and corresponding p-value of 0.000 strongly reject the null-hypothesis, suggesting that the instrumental variables are appropriately identified (i.e., correlated with the endogenous variable) and relevant (Kleibergen & Paap, 2006).

The second test is a Stock-Yogo (2005) test to evaluate weak identification which arises when excluded instruments are correlated with the endogenous regressors, but only weakly. Instruments are perceived as “weak” when they fall below the critical values as documented by Stock & Yogo (2005). Weak instruments can be identified by Kleibergen-Paap *rk* Wald F-statistics or Cragg-Donald F-statistics. Given the heteroskedastic nature of the dataset and the resulting robust standard errors incorporated in this study, the Kleibergen-Paap *rk* Wald F-statistics is deemed more appropriate to assess weak identification (Stock & Yogo, 2005). The null-hypothesis states weak identification of the instruments. The results of this test, displayed in Table 5, yield a Kleibergen-Paap *rk* Wald F-statistic of 2,634.218, significantly surpassing the thresholds of 7.800 (25% maximal IV size) set by Stock & Yogo (2005). Consequently, it can be concluded that the chosen instruments exhibit a robust correlation with the endogenous variable, thereby mitigating the risk of bias associated with weak instruments.

The final test employed to check the validity of the instruments is the Sargan-Hansen test, assessing overidentification (Hansen, 1982). The joint null-hypothesis states that the instruments are valid instruments (i.e., uncorrelated with the error term) and that the excluded instruments are correctly excluded from the estimated equation. The results are displayed in Table 5. The Hansen-J Chi-squared statistic of 2.171 and corresponding p-value of 0.338 suggest that the null-hypothesis cannot be rejected, thereby confirming the validity of the instruments selected for this study.

The results of the first stage of the 2SLS analysis can be found in Table 15 (Appendix D), depicting the relationship between the chosen instruments and the control variables and the endogenous variable (post-Covid time dummy). Notably, all three instruments are positively significantly related to the endogenous variable at the 1% significance level, indicating relevance of the respective instruments and thereby setting a strong foundation for the second stage where the predicted values of the endogenous variable will be used.

The second stage results are displayed in Table 5, Column 1. Notably, the negative relationship between the post-Covid time period and the proportion of the M&A transaction that is debt-funded becomes significant in the 2SLS model, suggesting that after controlling for endogeneity, it can be concluded that transactions in the post-Covid period have reduced reliance on debt financing. Furthermore, it should be noted that for almost all significant variables the significance and direction of the relationship remains equal across the OLS and 2SLS models. Only *Horizontal* becomes marginally significant in the 2SLS model, compared to the OLS model. By adjusting for potential endogeneity in the OLS model, the 2SLS provides a more accurate and theoretically sound basis for drawing conclusions. Consequently, the first Hypothesis cannot confidently be rejected and therefore it can be concluded that a reduced reliance on debt financing in the post-Covid time period has indeed occurred.

Comparison with the cash and equity models leaves ambiguous conclusions. In line with the first Hypothesis, the coefficients for the independent variables in the cash and equity models indeed display positive relationships. However, given the insignificance of these coefficients it cannot confidently be concluded that the reduced reliance on debt financing is indeed offset by an increase in cash- or equity-based funding, even after controlling for endogeneity. This further highlights the complex interplay between M&A financing structures in the post-Covid time period and provides solid avenue for further research to identify factors explaining the mechanisms currently not incorporated in the models.

Table 5: Second stage 2SLS IV regression results Hypothesis 1			
	(1)	(2)	(3)
	Debt	Cash	Equity
Covid	-0.008*	0.004	0.014
	(0.004)	(0.016)	(0.015)
Size	-0.005***	0.060***	-0.053***
	(0.001)	(0.005)	(0.004)
Profitability	-0.000	0.008***	-0.008***
	(0.000)	(0.001)	(0.001)
Leverage	0.024**	0.113***	-0.152***
	(0.011)	(0.026)	(0.025)
Leverage_c	0.011	0.096***	-0.110***
	(0.009)	(0.021)	(0.021)
Liquidity	0.001	0.001	-0.000
	(0.001)	(0.004)	(0.004)
Growth options	-0.006***	0.017***	-0.010**
	(0.001)	(0.005)	(0.004)
Age	0.000	0.0006***	-0.001***
	(0.000)	(0.000)	(0.000)
Deal value	-0.002*	-0.051***	0.046***
	(0.001)	(0.005)	(0.004)
Cross-border	0.011*	0.007	-0.020
	(0.006)	(0.014)	(0.013)
Target listed	-0.018**	-0.062	0.105
	(0.008)	(0.080)	(0.082)
Horizontal	-0.007*	-0.053***	0.057***
	(0.004)	(0.012)	(0.012)
S&P500_r	0.000	0.000	-0.000
	(0.000)	(0.001)	(0.001)
CCI_c	-0.000	0.001	-0.000
	(0.000)	(0.001)	(0.000)
GDP_g	0.001	0.002	-0.002
	(0.001)	(0.004)	(0.003)
	(0.012)	(0.024)	(0.023)
Industry FE	Controlled	Controlled	Controlled
Constant	0.121***	0.838***	0.067
	(0.019)	(0.093)	(0.094)
Kleibergen-Paap *rk* LM statistic	1,092.814	1,092.814	1,092.814
(p-value)	(0.000)	(0.000)	(0.000)
Kleibergen-Paap *rk* Wald F-statistic	2,634.218	2,634.218	2,634.218
Hansen J Chi-squared statistic	2.171	0.836	1.504
(p-value)	(0.338)	(0.658)	(0.472)
Observations	3,295	3,295	3,295
Adj. R-squared	0.041	0.361	0.378

Note: this table provides the results of the second stage of the 2SLS regression analysis. The first Column represents results of the debt model, while the second and third Column displays the results of the cash and equity models. The analysis is a 2SLS IV regression analysis, with *VIX, CPI_c* and *Fund rate* as the instrumental variables. Covid represents a dummy variable equal to 1 if the transaction takes place in the post-Covid period. The post-Covid period comprises the years 2020 – 2023, while the pre-Covid period consists of the years 2013 – 2019. A negative coefficient of the independent variable implies that transactions in the post-Covid period have a reduced reliance on the respective financing instrument. The regressions control for industry-fixed effects. Robust standard errors are displayed in parentheses. The null-hypotheses of the Kleibergen-Paap *rk* LM statistic and the Kleibergen-Paap *rk* Wald F-statistic state under-identified and weak instruments, respectively. The joint null-hypothesis of the Sargan-Hansen test states that the instruments are valid instruments and that the excluded instruments are correctly excluded from the estimated equation. Significance levels are denoted as * for 10%, ** for 5% and *** for 1%.

6.2 M&A financing and sectoral differences

6.2.1 OLS regression analysis

Table 16 in Appendix D presents the OLS regression results examining the relationship between the financing structure of an M&A transaction and the post-Covid period across various industries. The results present the outcome of the OLS regression analysis as denoted in Formula 3. The post-Covid time dummy variable has a positive yet statistically insignificant coefficient (0.026), suggesting that the post-Covid time period did not significantly affect the level of debt financing employed across all industries. The interaction terms between the post-Covid time dummy and the respective industries are all statistically insignificant, indicating that the effect of debt financing in the post-Covid period did not significantly differ across sectors. A Wald joint significance test is employed to test Hypothesis 2a, where the null-hypothesis states that all of the coefficients are equal to zero. This test yields an F-statistic of 0.600 and a corresponding p-value of 0.874, indicating that the null-hypothesis cannot be rejected at conventional significance levels. Therefore, it can be concluded that the post-Covid period effect on debt financing in M&A transactions is homogeneous across industries.

To elucidate further, a second regression analysis is performed, where industries are classified as either “Stable” or “Unstable” (refer to Appendix A for classification). The results dissected in Table 6 present the outcome of Formula 4. The negative coefficient for the post-Covid time dummy (-0.006) implies a reduction in the proportion of debt financing in M&A, although this effect is not statistically significant. The positive, yet statistically insignificant coefficient of the Industry class dummy (0.005) variable suggests that unstable industries have a positive but neglectable effect on debt financing in M&A. Notably, the coefficient of the interaction term between the post-Covid time period and unstable industries (0.005) is insignificant. Based on the OLS model, it can be concluded that there is no clear evidence that the post-Covid impact on debt financing differentiates between stable and unstable industries.

When comparing the debt to the cash and equity models, it can be observed that most of the variables remain their significance across all three models. The post-Covid time dummy displays a negative but statistically insignificant relationship across the debt and cash models (Column 1 and 2), while displaying a significant positive correlation in the equity model (Column 3), indicating an increased propensity towards equity financing in the post-Covid period according to this model. Notably, the industry classification dummy presents a stark contrast across the models. While it displays an insignificant positive relation in the debt model (0.005), it significantly influences the cash model (-0.156) and equity model (0.159). This indicates that unstable industries are less likely to use cash, but more likely to use equity for financing M&A transactions in the post-Covid investment climate. This may be attributed to the high-risk, high-growth nature of unstable industry firms, capitalizing on their growth-trajectories and minimizing financial constraints inherent in debt financing. Lastly, the interaction term between the post-Covid time dummy and the unstable industry dummy is insignificant across all models. This supports the findings off the debt model that the hypothesized differential impact of the post-Covid period on financing structures between stable and unstable industries does not hold substantial empirical support following an OLS analysis.

When looking at the control variables, it can be concluded that larger firms (*Size)* employ less debt financing and rely more on cash- and equity-based funding. Interestingly, *Leverage* and its change (*Leverage_c)* are significantly positive in the cash model, implying that firms with higher leverage or recent leverage increases prefer cash financing. This resonates with the argument that firms may utilize their inherent debt capacity to raise liquidity and subsequently pay for their M&A in cash, letting these transactions be recorded as cash-paid while they are inherently debt-funded. Finally, firms with higher growth opportunities (*Growth options)* prefer cash or equity funding over debt financing.

Table 6: OLS regression results Formula 4			
	(1) Debt	(2) Cash	(3) Equity
Covid	-0.006	-0.027	0.040*
	(0.006)	(0.023)	(0.021)
Industry class	0.005	-0.156***	0.159***
	(0.005)	(0.017)	(0.016)
Covid * Industry class	0.005	0.025	-0.029
	(0.008)	(0.027)	(0.025)
Size	-0.006***	0.046***	-0.038***
	(0.001)	(0.005)	(0.005)
Profitability	-0.000	0.008***	-0.008***
	(0.000)	(0.001)	(0.001)
Leverage	0.024**	0.101***	-0.142***
	(0.011)	(0.029)	(0.029)
Leverage_c	0.012	0.110***	-0.118***
	(0.010)	(0.023)	(0.023)
Liquidity	0.001	0.000	0.001
	(0.001)	(0.005)	(0.005)
Growth options	-0.003**	0.053***	-0.049***
	(0.001)	(0.005)	(0.005)
Age	0.000*	0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Deal value	-0.001	-0.048***	0.041***
	(0.001)	(0.005)	(0.005)
Cross-border	0.015**	0.047***	-0.060***
	(0.006)	(0.015)	(0.014)
Target listed	-0.031***	-0.162*	0.214**
	(0.008)	(0.083)	(0.084)
Horizontal	-0.006	-0.065***	0.068***
	(0.004)	(0.013)	(0.012)
S&P500_r	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)
CCI_c	-0.000	0.000	-0.000
	(0.000)	(0.001)	(0.001)
GDP_g	0.001	0.007*	-0.007*
	(0.001)	(0.004)	(0.004)
Industry FE	Controlled	Controlled	Controlled
Constant	0.084***	1.015***	-0.072
	(0.018)	(0.095)	(0.095)
Observations	2,923	2,923	2,923
Adj. R-squared	0.030	0.255	0.251

Note: this table provides the results of the OLS regression analysis with robust standard errors of the effect of the post-Covid time period on the funding structure of M&A transactions across various industries. Column 1 regresses the independent and control variables on the proportion of debt employed, whereas Column 2 and 3 regress the independent and control variables on the proportion of cash and equity employed. Covid represents a dummy variable equal to 1 if the transaction takes place in the post-Covid period. The post-Covid period comprises the years 2020 – 2023, while the pre-Covid period consists of the years 2013 – 2019. Industry class is a dummy variable equal to 1 if the industry is classified as unstable. A negative coefficient of the interaction term implies that transactions in unstable industries reduced reliance on the respective financing instrument in the post-Covid time period. The regressions control for industry-fixed effects. Robust standard errors are displayed in parentheses. Significance levels are denoted as * for 10%, ** for 5% and *** for 1%.

6.2.2 2SLS regression analysis

Since it has been established that endogeneity poses a challenge when employing an OLS model for definitive inferences regarding the hypotheses, the original OLS model is complemented with a 2SLS analysis to facilitate a more robust conclusion on Hypothesis 2b. The methods and instruments employed in this IV analysis are equal to those dissected in Section 6.1.2. The results are displayed in Table 7. The test statistics of the Kleibergen-Paap rk LM test, Stock-Yogo test and Sargan-Hansen test indicate that all instruments used in the analysis are appropriately identified, not weak and relevant. The dummy variable for the post-Covid time period no longer shows a significant relationship with the amount of debt financing applied. The significant positive coefficient for the unstable sector dummy (0.083) indicates that unstable industries tend to use slightly more debt in comparison to stable industries. Notably, the negative coefficient for the interaction term between the post-Covid period and unstable sectors (-0.011) implies that firms in unstable industries tend to employ 1.1 p.p. less debt in their financing structures in the post-Covid period compared to stable sectors. Consequently, this study finds support for Hypothesis 2b and concludes that the shift towards lower debt reliance is more pronounced in unstable sectors compared to stable sectors after controlling for endogeneity. These conclusions highlight the important interplay between industry stability and financing choices, with firms in unstable sectors being more likely to seek mitigation of financial risks in uncertain times. In addition, this further underscores the importance for policymakers and financial institutions to tailor their support programs to shield industries that are more vulnerable from the repercussions of large economic disruptions.

The insignificant coefficients in the cash and equity models again give insufficient proof that the reduced reliance on debt financing is offset by an increased reliance on cash- or equity-based funding after controlling for endogeneity.

Table 7: Second stage 2SLS IV regression results Hypothesis 2b			
	(1)	(2)	(3)
	Debt	Cash	Equity
Covid	0.094	0.173	-0.091
	(0.086)	(0.296)	(0.279)
Industry class	0.083*	-0.0056	-0.005
	(0.045)	(0.143)	(0.136)
Covid * Industry class	-0.011**	0.003	0.024
	(0.006)	(0.023)	(0.022)
Size	-0.005***	0.060***	-0.053***
	(0.001)	(0.005)	(0.005)
Profitability	-0.000	0.008***	-0.007***
	(0.000)	(0.001)	(0.001)
Leverage	0.027**	0.108***	-0.147***
	(0.011)	(0.028)	(0.027)
Leverage_c	0.013	0.103***	-0.113***
	(0.010)	(0.022)	(0.022)
Liquidity	0.001	-0.001	0.001
	(0.001)	(0.004)	(0.004)
Growth options	-0.006***	0.020***	-0.015***
	(0.001)	(0.005)	(0.008)
Age	0.000	0.001**	-0.001***
	(0.000)	(0.000)	(0.000)
Deal value	-0.001	-0.052***	0.046***
	(0.001)	(0.005)	(0.005)
Cross-border	0.013**	0.016	-0.029**
	(0.006)	(0.015)	(0.014)
Target listed	-0.021**	-0.074	0.118
	(0.008)	(0.083)	(0.085)
Horizontal	-0.008*	-0.051***	0.056***
	(0.005)	(0.013)	(0.013)
S&P500_r	0.000	0.000	-0.000
	(0.000)	(0.001)	(0.001)
CCI_c	-0.000	0.001	-0.000
	(0.000)	(0.001)	(0.001)
GDP_g	0.000	0.002	-0.002
	(0.001)	(0.004)	(0.004)
Industry FE	Controlled	Controlled	Controlled
Constant	0.112***	0.857***	0.058
	(0.020)	(0.0970)	(0.099)
Kleibergen-Paap *rk* LM statistic	768.964	768.964	768.964
(p-value)	(0.000)	(0.000)	(0.000)
Kleibergen-Paap *rk* Wald F-statistic	696.453	696.453	696.453
Hansen J Chi-squared statistic	0.496	0.424	2.454
(p-value)	(0.780)	(0.809)	(0.293)

Observations	2,923	2,923	2,923
Adj. R-squared	0.030	0.255	0.251

Note: this table provides the results of the second stage of the 2SLS regression analysis. The first Column represents results of the debt model, while the second and third Column displays the results of the cash and equity models. The analysis is a 2SLS IV regression analysis, with *VIX, CPI_c* and *Fund rate* as the instrumental variables. Covid is a dummy variable equal to 1 if the transaction takes place in the post-Covid period. Industry class is a dummy variable equal to 1 if the acquirer industry is classified as unstable. A negative coefficient of the independent variable implies that transactions in unstable industries in the post-Covid period have a reduced reliance on the respective financing instrument. The regressions control for industry-fixed effects. Robust standard errors are displayed in parentheses. The null-hypotheses of the Kleibergen-Paap *rk* LM statistic and the Kleibergen-Paap *rk* Wald F-statistic state under-identified and weak instruments, respectively. The joint null-hypothesis of the Sargan-Hansen test states that the instruments are valid instruments and that the excluded instruments are correctly excluded from the estimated equation. Significance levels are denoted as * for 10%, ** for 5% and *** for 1%.

6.3 Robustness checks

6.3.1 Logistic regression analysis

In order to cope with the heteroskedastic nature of the dataset employed in this study, a logistic regression analysis is employed to check the robustness of the OLS regression results. Contrary to OLS regressions, logistic regressions do not assume that the residuals are normally distributed, have a mean of zero and constant variance (homoskedasticity). In addition, logistic regressions do not assume a linear relationship between the independent and dependent variables (Hill et al., 2018). In acquisition financing, the logistic model assumes that the bidder chooses a source of financing from one of the available categories (Martynova & Renneboog, 2009). In the context of this study, the logistic model is used to estimate the probability that in a specific deal debt financing is applied. The corresponding regression formula is specified as follows:

$$\ln\left(\frac{P(dDebt_i = 1)}{1 - P(dDebt_i = 1)}\right) = \beta_0 + \beta_1 dCovid_i + \theta Controls_i + \psi Industry_i + \varepsilon_i \quad (7)$$

where $dDebt_i$ is a dummy variable equal to 1 if the specific transaction involves debt financing. As such, $\ln\left(\frac{P(dDebt_i=1)}{1-P(dDebt_i=1)}\right)$ represents the log odds of the dependent variable being 1 (i.e., there is debt financing applied in the funding structure of the M&A transaction), when all independent variables are 0.

Notably, the interpretation of the coefficient of the independent variable is different in logistic regression models compared to OLS regression models. Whereas the coefficient of the independent variable in an OLS regression should be interpreted as the average change in the dependent variable for a one-unit change in the independent variable, the output of the logistic regression model should be interpreted as the change in log odds of the dependent variable for a one-unit change in the independent variable. In the context of this study, the OLS coefficient should be interpreted as the p.p. change in the proportion of debt financing in the post-Covid period, while the logistic coefficient should be interpreted as the change in the probability that debt financing is applied in the post-Covid period.

The results of the logistic regression analysis are displayed in Column 2 of Table 8. When looking at the Pseudo R-squared, it can be observed that the logistic model results in a moderate improvement in explanatory power, suggesting that a logistic approach might be a better method of explaining debt financing in the post-Covid era. In addition, it is observed that some of the variables that are significant in the OLS model (Column 1) retain both their significance and direction in the logistic model (Column 2), whereas others exhibit significant relationships in only one of the two models. The independent variable, *Covid*, changes sign in the logistic model in comparison to the OLS model, indicating that the chances of debt financing in the post-Covid period are higher compared to the pre-Covid period. Yet, since the coefficient in both models are not statistically significant, no definitive conclusions on this relationship can be drawn.

6.3.2 Tobit regression analysis

To address the anomalous characteristics observed in the data for the dependent variable, this study employs a Tobit regression analysis to check the robustness of the OLS regression results. Theoretically, the value of the variables *Debt, Cash, Equity* and *Other* can range between 0 and 1, meaning that a transaction can be financed anywhere between 0% and 100% through the respective financing instruments. In addition, the sum of the proportions should equal 1. When observing Table 3 it can be established that the values of these variables do not exhibit their theoretical nature. In data cleaning, this study set the assumption that the sum of the financing proportions should be above 0.95 but below 1.05 to account for the possibility of rounding errors. While this improves the validity of the dataset, the data within this study still exhibits values above 1, which are not feasible in practical terms. Tobit regression analysis can account for this by treating these values as censored observations, providing more accurate and unbiased estimates than OLS regression, which would treat these out-of-bound values as actual observations (Vermaelen & Xu, 2014; Hill et al., 2018).

The interpretation of the Tobit regression model in the context of this study is similar to the OLS regression model in that it tries to predict the proportion of debt financing applied in M&A transactions, while accounting for a censored dependent variable. As such, the Tobit regression model applied is as follows:

$$debt_i^* = \beta_0 + \beta_1 dCovid_i + \theta Controls_i + \psi Industry_i + \varepsilon_i \tag{8}$$

where $debt_i^*$ is the latent variable representing the underlying propensity for the proportion of the transaction that is financed through debt. The term "latent" means that the variable is subject to censoring. This study employs a dependent variable which is censored to fall within the 0 – 1 range.

The results of the Tobit regression analysis are displayed in Column 3 of Table 8. Again, a moderate enhancement in the model's explanatory power is observed, evidenced by a Pseudo R-squared of 14.7%, which represents an improvement over the 4.2% observed in the OLS model. Furthermore, most variables that are significant in the OLS model (Column 1) maintain their significance and sign of the correlation. The sole discrepancies observed relate to the variables *Deal value* and *Target listed* as they show negative significant relationships in the OLS model, yet are no longer significant in the Tobit model, suggesting no significant relationship between debt financing and the deal value or the target being public according to the Tobit regression model. As with the logistic model, the independent variable, *Covid*, changes sign in the Tobit model compared to the OLS model, while remaining insignificant. This suggests that while the post-Covid period might have some influence on the latent propensity to use debt funding, this relationship is not strong enough to be significant and hence conclusive inferences on this relationship cannot be established based on the Tobit model.

Table 8: Robustness check regression results			
	(1) Debt *(OLS)*	(2) dDebt *(Logit)*	(3) Debt *(Tobit)*
Covid	-0.001	0.194	0.023
	(0.004)	(0.207)	(0.076)
Size	-0.005***	-0.377***	-0.136***
	(0.001)	(0.063)	(0.025)
Profitability	-0.000	0.014**	0.004*
	(0.000)	(0.006)	(0.002)
Leverage	0.024**	0.519	0.233**
	(0.011)	(0.319)	(0.118)
Leverage_c	0.011	0.384*	0.181**
	(0.010)	(0.218)	(0.079)
Liquidity	0.001	0.044	0.017
	(0.001)	(0.052)	(0.019)
Growth options	-0.006***	-0.283***	-0.103***
	(0.001)	(0.076)	(0.028)
Age	0.000	-0.001	-0.000
	(0.000)	(0.004)	(0.002)
Deal value	-0.002*	-0.045	-0.019
	(0.001)	(0.064)	(0.024)
Cross-border	0.011*	0.369*	0.187**
	(0.006)	(0.210)	(0.076)
Target listed	-0.018**	-0.690	-0.147
	(0.008)	(1.667)	(0.405)
Horizontal	-0.007	-0.130	-0.074
	(0.004)	(0.184)	(0.067)
S&P500_r	0.000	-0.004	-0.001
	(0.000)	(0.009)	(0.003)
CCI_c	-0.000	-0.003	-0.001
	(0.000)	(0.008)	(0.003)
GDP_g	0.000	0.044	0.009
	(0.001)	(0.057)	(0.021)
Industry FE	Controlled	Controlled	Controlled
Constant	0.122***	1.689	0.392
	(0.019)	(1.741)	(0.465)
Observations	3,295	3,239	3,295
(Pseudo) Adj. R-squared	0.042	(0.135)	(0.147)

Note: this table provides the results of the different regression analyses. Column 1 represents an OLS model, while Column 2 and 3 employ logistic and Tobit regression models. The first and third model try to predict the proportion of debt financing used in an M&A transaction, while the second model tries to predict the probability of debt financing to be applied in a specific M&A transaction. Covid represents a dummy variable equal to 1 if the transaction takes place in the post-Covid period. A negative coefficient of the independent variable implies that transactions in the post-Covid period have a reduced reliance on (model 1 and 3) or probability of (model 2) debt financing. The regressions control for industry-fixed effects. Robust standard errors are displayed in parentheses. Significance levels are denoted as * for 10%, ** for 5% and *** for 1%.

6.3.3 Sensitivity analysis

A closer examination of the dataset reveals that the descriptive statistics pertaining to M&A transactions in the year 2023 exhibit notable deviations from those of preceding years. Remarkably, the number of observations in 2023 is equal to 64, which is substantially less than the number of transactions in any other year, with the next lowest year in terms of transaction volume being 2013 at 253 observations. Furthermore, the median acquirer market capitalization in 2023 is over 3.5 times higher than the average of earlier years. Similarly, the median deal value in 2023 surpasses the average of prior years by a factor of almost 4. Given the potential for the fiscal year 2023 data to be incomplete, particularly if some companies' financial statements have not yet been audited at the time of this study, the inclusion of this year in the analysis may compromise the reliability of the study. Therefore, this study performs a sensitivity analysis by omitting the year 2023 from the post-Covid period. Consequently, the revised period classification designates the years 2013 – 2019 as the pre-Covid period and 2020 – 2022 as the post-Covid period. The results of these analyses under this revised classification are displayed in Table 17 of Appendix D.

The results display an overall consistency of the models' findings compared to the regression results when the year 2023 is included in the dataset. Again, an introduction of a negative significant coefficient of the post-Covid time dummy is observed in the 2SLS model. The observed significance lies at the 5% level, as compared to 10% in the original model. Accordingly, it can be concluded that the post-Covid time period is indeed characterized by a reduced reliance of debt funding in M&A transactions when controlling for endogeneity.

7. Conclusion and discussion

This section consolidates the primary findings of this paper as well as its academic and practical implications. In addition, it addresses limitations inherent in the study and proposes avenues for further research.

This study investigated if and how the financing composition of M&A transactions has been impacted by the changing financing climate in the aftermath of the Covid-19 pandemic. The post-pandemic period is characterized by enhanced government spending, rising inflation and subsequently rising interest rates, with the FFR rising from near-zero in 2020 up to 5.5% in 2023. This study tried to assess the extent to which these macroeconomic changes have reshaped the financing composition of M&A activities. Specifically, the aim of this paper is to assess if a reallocation among specific financing instruments such as debt, cash and equity has occurred and whether this potential reallocation is stronger in certain sectors compared to others. Consequently, this study provides a solid contribution to the existing body of literature on M&A and MoP, by analyzing the impact of significant macroeconomic shifts during the post-Covid era on M&A dynamics, thereby enriching our comprehension of corporate adaptability and strategic realignments in response to economic turbulence.

To provide a comprehensive analysis, this study utilized a sample of 3,295 transactions of US acquirers over the period 2013 – 2023. The years 2013 – 2019 are classified as the pre-Covid period, while the post-Covid period constitutes the years 2020 – 2023. The financing structure of acquiring firms is measured by the proportion of the transaction that is financed through debt. The independent variable in this study is a post-Covid time dummy variable equal to 1 if the transaction occurred in the post-pandemic period. To reduce the effect of omitted variables, this study controls for various firm-specific, deal-specific, macroeconomic and industry-fixed effects.

The main results of this study reveal that there is indeed a shift in the financing structure of M&A deals in the post-Covid time period with a reduced reliance on debt funding in these transactions. While the original OLS model shows a negative yet insignificant coefficient, this relationship becomes significantly negative when controlling for endogeneity in the 2SLS model. As the econometric rigor of the 2SLS is perceived as superior to the original OLS model, this study finds support for the first Hypothesis. Consequently, it can be concluded that the post-Covid financing climate has significantly moved away from traditional debt financing. Further analysis with cash- and equity-based financing models leaves inconclusive remarks.

Both the original OLS model and the 2SLS model display a positive relationship between cash and equity financing in the post-pandemic period, yet the insignificance of these relationships raises questions regarding what has offset the reduced reliance of debt financing in the post-Covid period. This gap in understanding presents ample opportunity for researchers to further explore the shift in financing mechanisms in this time period.

A further investigation of the post-Covid effect on M&A financing across industries reveals that the absence of such a relationship based on the OLS model is homogenous across sectors. Contrary, a significantly positive relationship between equity financing in the post-Covid period can be established when considering industry stability. This indicates that firms increase their equity proportions in M&A financing in the post-Covid period. In addition, based on the OLS model it can be established that unstable firms utilize significantly less cash and more equity financing in their funding structures, potentially due to risk management considerations. In addition, after controlling for endogeneity, this study documents support for Hypothesis 2b by finding that firms in unstable industries have a more pronounced divergence from traditional debt financing in the post-Covid period in comparison to firms in stable industries. Control variables such as, *Size, Leverage, Growth options, Deal value, Cross-border* and *Target listed* also show significant relationships with debt financing, further underscoring the complex relationship between financing choices and macroeconomic conditions. Performing a robustness check and sensitivity analysis by incorporating logistic and Tobit regression analyses and excluding the potentially biased year 2023 from the sample yields similar results to the original OLS model, depicting insignificant relationships.

From a practical perspective, this study provides valuable insights into corporate adaptability in light of economic instability. Specifically, this study shows that in light of economic upheaval after the Covid pandemic, firms adjust their financing choices in M&A transactions and rely less on costly debt financing. This adaptability implies that firms consistently monitor their financing positions and try to remain flexible in changing economic conditions. In addition, a reduced reliance on debt financing, especially in unstable industries, implies that firms try to avoid costly financing or try to share the risks associated with economic turbulence. For policymakers and financial institutions these findings underscore the significant impact of their policies on corporate finance decisions and indicate a potential need for support programs in those industries that respond more strongly to economic turbulence.

Naturally, this study exhibits several limitations. Firstly, despite efforts made to control for potential endogeneity by performing a 2SLS IV regression analysis, the risk of residual endogeneity within the model cannot be discounted. This may arise from various sources, including measurement error or selection bias where only companies with strong liquidity positions – thereby possessing a greater capacity for debt attraction – become acquirers. Alternatively, the exclusion of various significant variables from the model could lead to omitted variable bias. This concern is further underscored by the relatively low R-squared (4.2%) of the original model, highlighting that the current study setup has relatively low explanatory power. Furthermore, the rather low number of observations in the final year of this study may bias the results. Additionally, the limited sample size relating to transactions that involved debt financing available in BvD's Orbis database further diminishes the statistical robustness of the model and the reliability of its findings. Consequently, some avenues for further research include broadening the dataset to encompass a more diverse set of transactions and jurisdictions, thereby strengthening the study's robustness and generalization across various contexts. Furthermore, comparative analysis of corporate adaptability to various economic shocks, such as the GFC or Brexit, could yield an even deeper understanding into how firms adjust their financing strategies in response to economic instability. Lastly, further examination may extend beyond M&A investments to include other substantial corporate investments such as those in (financial) technology or ESG factors, offering more holistic insights into corporate adaptability in times of economic turbulence.

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9. Appendices

9.1 Appendix A

Table 9: Industry classification

	Classification
Food Products	Stable
Recreation	Unstable
Healthcare, Medical Equipment, Pharmaceutical Products	Unstable
Chemicals	Stable
Construction and Construction Materials	Unstable
Fabricated Products and Machinery	Stable
Petroleum and Natural Gas	Unstable
Utilities	Stable
Communication	Stable
Personal and Business Services	Unstable
Business Equipment	Stable
Transportation	Unstable
Wholesale	Unstable
Retail	Unstable
Banking, Insurance, Real Estate, Trading	Unstable
Other	Omitted

Note: this table provides an overview of the classification of industries as "Stable" or "Unstable". Industries are classified as "Unstable" if they are highly innovative and involve high-risk, high-growth trajectories, if they are sensitive to interest rate changes or if their demand is strongly reactive to the economic cycle. Industries are classified as "Stable" if they provide essential services or if their demand is seen as inelastic to economic cycles.

9.2 Appendix B

Table 10: Breakdown of "Other" industries

	N	%	Cum.
Aircraft, ships, and railroad equipment	43	11.56	11.56
Apparel	17	4.57	16.13
Automobiles and Trucks	41	11.02	27.15
Beer & Liquor	5	1.34	28.49
Business Supplies and Shipping Containers	38	10.22	38.71
Coal	4	1.08	39.79
Consumer Goods	45	12.10	51.89
Electrical Equipment	29	7.80	59.69
Precious Metals, Non-Metallic, and Industrial Metal Mining	26	6.99	66.68
Printing and Publishing	19	5.11	71.79
Restaurants, Hotels, Motels	41	11.02	82.81
Steel Works Etc.	25	6.72	89.53
Textiles	6	1.61	91.14
Everything Else	33	8.87	100.00
Total	372	100.00	

Note: this table provides a detailed breakdown of the industries labeled as "Other". Industries represent Fama-French industry classifications based on SIC codes (Fama & French, 1997).

Table 11: Summary of regression statistics by dCovid						
Panel A: Pre-Covid period						
	N	Mean	SD	Min	Median	Max
Debt	2,086	0.018	0.104	0.000	0.000	1.000
Cash	2,086	0.714	0.397	0.000	1.000	1.046
Equity	2,086	0.242	0.382	0.000	0.000	1.000
Other	2,086	0.025	0.113	0.000	0.000	1.000
Total assets	2,086	18,442.526	83,745.684	0.065	2,852.155	2,415,690.000
Size	2,086	7.706	2.269	0.063	7.956	14.697
Profitability	2,086	0.207	12.886	-54.946	2.396	17.564
Leverage	2,086	0.787	0.279	0.193	0.770	1.556
Leverage_c	2,086	0.060	0.292	-0.584	0.012	1.352
Liquidity	2,086	2.167	1.651	0.409	1.721	9.568
Growth options	2,086	1.284	1.210	0.098	1.002	6.189
Age	2,086	26.727	25.993	0.000	20.000	112.000
Dealvalue_o	2,086	859.237	4,135.048	1.000	130.55	108700
Deal value	2,086	11.800	1.913	6.908	11.780	18.504
Cross-border	2,086	0.201	0.401	0.000	0.000	1.000
Target listed	2,086	1.005	0.069	0.000	0.000	1.000
Horizontal	2,086	0.631	0.483	0.000	1.000	1.000
S&P500_r	2,086	11.425	8.225	-6.567	12.533	29.601
CCI_c	2,086	10.614	11.352	-10.935	9.271	35.959
GDP_g	2,086	2.491	0.378	1.819	2.467	2.966
VIX	2,086	14.996	3.334	10.125	14.22	24.953
CPI_c	2,086	1.519	0.777	-0.200	1.660	2.950
Fund rate	2,086	0.944	0.821	0.250	0.500	2.500
Panel B: Post-Covid period						
	N	Mean	SD	Min	Median	Max
Debt	1,209	0.016	0.093	0.000	0.000	1.000
Cash	1,209	0.682	0.412	0.000	1.000	1.000
Equity	1,209	0.283	0.399	0.000	0.000	1.025
Other	1,209	0.019	0.097	0.000	0.000	1.000
Total assets	1,209	19,578.635	68,957.688	0.878	2993.327	1,188,140.000
Size	1,209	7.870	2.194	0.630	8.004	13.988
Profitability	1,209	-1.981	16.253	-54.946	2.037	17.564
Leverage	1,209	0.789	0.303	0.193	0.770	1.556
Leverage_c	1,209	0.061	0.358	-0.584	0.012	1.352
Liquidity	1,209	2.296	2.038	0.409	1.721	9.568
Growth options	1,209	1.562	1.509	0.098	1.002	6.189
Age	1,209	25.842	25.499	0.000	19.000	112.000
Dealvalue_o	1,209	1,197.803	4,206.092	1.000	212.900	69,000.000
Deal value	1,209	12.206	1.976	6.908	12.269	18.050
Cross-border	1,209	0.172	0.378	0.000	0.000	1.000
Target listed	1,209	1.010	0.099	0.000	0.000	1.000
Horizontal	1,209	0.587	0.493	0.000	1.000	1.000
S&P500_r	1,209	17.068	17.924	-19.953	17.617	62.715
CCI_c	1,209	1.844	23.130	-35.693	-3.247	39.697
GDP_g	1,209	2.594	3.139	-2.213	1.935	5.800
VIX	1,209	23.281	7.055	12.718	22.170	57.737
CPI_c	1,209	5.040	2.727	0.120	5.390	9.060
Fund rate	1,209	1.050	1.477	0.250	0.250	5.500

Note: this table provides a comprehensive breakdown of the final sample comprising 3,295 transactions over the years 2013 – 2023. The sample consists of publicly traded corporations in the US and industries represent Fama-French industry classifications based on SIC codes (Fama & French, 1997). Every industry with less than 50 observations is labeled as "Other", of which a detailed breakdown can be found in Table 10 of Appendix B. Panel A describes the pre-Covid period, while Panel B describes the post-Covid period.

9.3 Appendix C

Table 12: Augmented Dickey-Fuller test for non-stationarity

	Z(t)	p-value
S&P500	-0.246	0.933
CCI	-2.023	0.277
GDP	-0.036	0.956
VIX	-4.651***	0.000
CPI	5.694	1.000
Fund rate	1.622	0.998
S&P500_r	-3.919***	0.002
CCI_c	-3.892**	0.002
GDP_g	-5.399***	0.000
CPI_c	-1.060	0.731

Note: this table provides the test statistics and corresponding p-values of the Augmented Dickey-Fuller (ADF) test. Significance levels are denoted as * for 10%, ** for 5% and *** for 1%.

Table 13: Variance inflation factors

	VIF	1/VIF
Covid	1.396	0.717
Size	2.617	0.382
Profitability	1.486	0.673
Leverage	1.500	0.667
Leverage_c	1.034	0.967
Liquidity	1.567	0.638
Growth options	1.307	0.765
Age	1.186	0.843
Deal value	1.954	0.512
Cross-border	1.074	0.931
Target listed	1.047	0.955
Horizontal	1.147	0.872
S&P500_r	1.900	0.526
CCI_c	2.356	0.425
GDP_g	1.544	0.648
Mean VIF	2.196	

Note: this table provides the VIFs for all independent and control variables incorporated in this study.

Table 14: Pearson correlation coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1) Debt	1.000																		
(2) Covid	-0.010	1.000																	
(3) Size	-0.148***	0.035**	1.000																
(4) Profitability	-0.103***	-0.074***	0.498***	1.000															
(5) Leverage	0.039**	0.004	0.156***	0.005	1.000														
(6) Leverage_c	0.053***	0.000	-0.103***	-0.090***	0.027	1.000													
(7) Liquidity	0.001	0.034**	-0.214***	-0.142***	-0.531***	0.010	1.000												
(8) Growth options	-0.011	0.100***	-0.192***	-0.037**	-0.078***	0.001	0.213***	1.000											
(9) Age	-0.028*	-0.017	0.297***	0.258***	0.042**	-0.044**	-0.115***	-0.029*	1.000										
(10) Deal value	-0.120***	0.101***	0.663***	0.268***	0.123***	-0.010	-0.125***	-0.053***	0.181***	1.000									
(11) Cross-border	0.047***	-0.035**	-0.008	-0.012	0.016	0.016	0.021	0.134***	0.006	-0.001	1.000								
(12) Target listed	-0.013	0.030*	-0.055***	-0.105***	-0.034*	0.013	0.124***	0.020	-0.052***	-0.093***	-0.042**	1.000							
(13) Horizontal	-0.033*	-0.043**	0.082***	0.055***	0.017	-0.011	-0.079***	-0.080***	-0.004	-0.040**	0.017	-0.015	1.000						
(14) S&P500_r	-0.010	0.210***	-0.009	-0.014	-0.022	-0.038**	0.011	0.065***	-0.060***	-0.004	0.003	-0.008	0.566***	1.000					
(15) CCI_c	-0.008	-0.246***	-0.033*	0.025	-0.026	-0.050***	0.010	-0.024	-0.034**	-0.021	0.038**	-0.006	0.421***	0.497***	1.000				
(16) GDP_g	-0.004	0.026	-0.004	0.015	-0.005	-0.049***	-0.005	-0.022	-0.048***	-0.007	0.006	-0.016	-0.237***	-0.444***	-0.319***	1.000			
(17) VIX	-0.027	0.622***	0.031*	-0.046***	0.030*	0.017	0.023	0.047***	-0.005	-0.028*	-0.003	-0.019	0.115***	0.013	0.314***	0.317***	1.000		
(18) CPI_c	-0.020	0.694***	0.022	-0.048***	0.017	0.003	0.011	0.018	-0.016	0.012	-0.004	0.001	-0.414***	-0.226***	-0.073***	-0.019	0.236***		
(19) Fund rate	0.011	0.046***	0.049***	0.033*	0.031*	-0.002	-0.012	0.008	0.082***	0.051***	0.000	-0.023	0.001	-0.451***	-0.215***	-0.084***	-0.022	0.220***	1.000

Note: this table provides the Pearson correlation coefficients. Significance levels are denoted as * for 10%, ** for 5% and *** for 1%

9.4 Appendix D

Table 15: First stage 2SLS IV regression results

	(1) dCovid
VIX	0.031***
	(0.000)
CPI_c	0.099***
	(0.000)
Fund rate	0.040***
	(0.000)
Size	0.003
	(0.304)
Profitability	-0.001
	(0.001)
Leverage	-0.021
	(0.185)
Leverage_c	-0.012
	(0.323)
Liquidity	0.000
	(0.948)
Growth options	0.012***
	(0.000)
Age	0.000
	(0.733)
Deal value	0.004*
	(0.099)
Cross-border	-0.006
	(0.518)
Target listed	0.038
	(0.492)
Horizontal	-0.006
	(0.482)
S&P500_r	0.018***
	(0.000)
CCI_c	-0.009***
	(0.000)
GDP_g	-0.007*
	(0.040)
Industry FE	Controlled
Constant	-0.786***
	(0.000)
Observations	3,295

Note: this table provides the results of the first stage of the 2SLS regression analysis. *VIX, CPI_c* and *Fund rate* are included as the instrumental variables. The regressions control for industry-fixed effects. Robust standard errors are displayed in parentheses. Significance levels are denoted as * for 10%, ** for 5% and *** for 1%.

Table 16: OLS regression results Formula 3	
	(1)
	Debt
Covid	0.026
	(0.024)
Covid * Banking, Insurance, Real Estate, Trading	-0.029
	(0.025)
Covid * Business Equipment	-0.026
	(0.027)
Covid * Chemicals	-0.020
	(0.024)
Covid * Communication	-0.045
	(0.031)
Covid * Construction and Construction Materials	-0.036
	(0.025)
Covid * Fabricated Products and Machinery	-0.022
	(0.025)
Covid * Food Products	-0.051
	(0.032)
Covid * Personal and Business Services	-0.031
	(0.026)
Covid * Petroleum and Natural Gas	-0.033
	(0.027)
Covid * Recreation	-0.029
	(0.025)
Covid * Retail	-0.028
	(0.028)
Covid * Transportation	-0.020
	(0.053)
Covid * Utilities	-0.033
	(0.025)
Covid * Wholesale	-0.031
	(0.032)
Covid * Other	-0.028
	(0.026)
Size	-0.0053***
	(0.001)
Profitability	-0.0001
	(0.000)
Leverage	0.024**
	(0.011)
Leverage_c	0.012
	(0.010)
Liquidity	0.001
	(0.001)
Growth options	-0.006***
	(0.001)
Age	0.000
	(0.000)
Deal value	-0.002*

	(0.001)
Cross-border	0.010*
	(0.006)
Target listed	-0.018**
	(0.008)
Horizontal	-0.007
	(0.004)
S&P500_r	0.000
	(0.000)
CCI_c	-0.0000
	(0.000)
GDP_g	0.000
	(0.001)
Industry FE	Controlled
Constant	0.112***
	(0.020)
Observations	3,295
Adj. R-squared	0.039

Note: this table provides the results of the OLS regression analysis with robust standard errors of the effect of the post-Covid time period on the funding structure of M&A transactions across various industries. Covid represents a dummy variable equal to 1 if the transaction takes place in the post-Covid period. The post-Covid period comprises the years 2020 – 2023, while the pre-Covid period consists of the years 2013 – 2019. The regression incorporates an interaction term between the post-Covid dummy and the respective industries to test the differential effect of the post-Covid period by industry. The regressions control for industry-fixed effects. Robust standard errors are displayed in parentheses. Significance levels are denoted as * for 10%, ** for 5% and *** for 1%.

Table 17: Sensitivity check regression results				
	(1)	(2)	(3)	(4)
	Debt	dDebt	Debt	Debt
	(OLS)	*(Logit)*	*(Tobit)*	*(2SLS)*
Covid	-0.003	0.057	-0.027	-0.009**
	(0.004)	(0.212)	(0.08)	(0.004)
Size	-0.005***	-0.376***	-0.138***	-0.005***
	(0.001)	(0.064)	(0.026)	(0.001)
Profitability	-0.000	0.013**	0.004*	-0.000
	(0.000)	(0.006)	(0.002)	(0.000)
Leverage	0.025**	0.538*	0.245**	0.025**
	(0.011)	(0.325)	(0.121)	(0.011)
Leverage_c	0.011	0.377*	0.179**	0.011
	(0.010)	(0.223)	(0.081)	(0.010)
Liquidity	0.001	0.043	0.017	0.001
	(0.001)	(0.052)	(0.020)	(0.001)
Growth options	-0.006***	-0.285***	-0.105***	-0.006***
	(0.001)	(0.077)	(0.029)	(0.001)
Age	0.000	-0.001	-0.000	0.000
	(0.000)	(0.004)	(0.002)	(0.000)
Deal value	-0.002*	-0.048	-0.020	-0.002*
	(0.001)	(0.065)	(0.025)	(0.001)
Cross-border	0.011*	0.379*	0.195**	0.011*
	(0.006)	(0.213)	(0.079)	(0.006)
Target listed	-0.018**	-0.683	-0.147	-0.018**
	(0.008)	(1.641)	(0.412)	(0.008)
Horizontal	-0.007	-0.124	-0.076	-0.007*
	(0.004)	(0.187)	(0.069)	(0.004)
S&P500_r	0.000	0.001	0.001	0.000
	(0.000)	(0.009)	(0.003)	(0.000)
CCI_c	-0.000	-0.006	-0.002	-0.000*
	(0.000)	(0.008)	(0.003)	(0.000)
GDP_g	0.000	0.049	0.010	0.001
	(0.001)	(0.058)	(0.021)	(0.001)
Industry FE	Controlled	Controlled	Controlled	Controlled
Constant	0.121***	1.657	0.380	0.120***
	(0.020)	(1.723)	(0.475)	(0.020)
Observations	3,231	3,231	3,231	3,231
(Pseudo) Adj. R-squared	0.042	(0.135)	(0.147)	0.041

Note: this table provides the results of the different regression analyses. The first model presents an OLS regression, while the second, third and fourth model represent a logistic, Tobit and 2SLS IV regression, respectively. The first, third and fourth model predict the proportion of debt financing used, while the second model predicts the probability of debt financing being applied. Covid represents a dummy variable equal to 1 if the transaction takes place in the post-Covid period (2020 – 2023). A negative coefficient of the independent variable implies that transactions in the post-Covid period have a reduced reliance on (model 1, 3 and 4) or probability of (model 2) debt financing. The regressions control for industry-fixed effects. Robust standard errors are displayed in parentheses. Significance levels are denoted as * for 10%, ** for 5% and *** for 1%.