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Master Thesis Financial Economics

A Study on the Impact of Monetary Policy on the U.S. M&A Market

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Abstract

This paper examines the relationship between interest rates and several aspects of U.S. mergers and acquisitions (M&A). The results indicate a negative relationship between interest rates and acquirer debt, in line with the findings by Acharya et al. (2022) and corresponding with the interest rate effect as theorized by Baldwin (2022). Furthermore, this paper finds a non-significant relationship between interest rates and target multiples, which contradicts findings by Horn & Fischer (2021) and Bromley & Zhou (2011). Lastly, the evidence suggests that there does not exist a relationship between acquirer performance and interest rates which contradicts the findings by Adra et al. (2020). This paper provides important insight for both academics and practitioners in understanding the impact of interest rates on M&A transactions.

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1. Introduction

Over the past decades, the U.S. has experienced several crises. Usually, the U.S. Federal Reserve responds by lowering the federal funds rate like in the 1987 market crash or 2000 dot-com bubble (Nygaard, 2020; Langdana, 2009). When the sub-prime mortgage crisis hit the world in 2008, a combination of lower federal funds rates and quantitative easing was used to stimulate the economy. Over the decade following the crisis, the M&A market seemed to thrive from the low interest rate environment with deal value and volume surging (McKinsey, 2022). More recently, the Covid-19 crisis caused federal reserves and central banks all around the world to turn towards lower interest rates and quantitative easing to stimulate their economies. One country that was especially aggressive in their monetary policy approach was the United States. As a result of this money creation, 80% of all US dollars currently in circulation have been printed in the last 2 years (Federal Reserve, 2022). At the same time, the M&A market was booming with multiples reaching all-time highs (Bain & Company, 2022).

More recently, this boom has started to come to a screeching halt with deal value dropping more than 10% in the first half of 2022 (McKinsey & Co, 2022). The period of low interest rates has also come to its end with the federal reserve increasing interest rates to 3.15% as of the end of September 2022 (U.S. Federal Reserve, 2022). This monetary policy measure is meant to combat the excessive current inflation as the U.S. Consumer Price Index rose to 8.2% as of September 2022 (U.S. Bureau of Labour Statistics, 2022). With all these changes in macroeconomic policy and the state of the M&A market, one cannot help but start to wonder whether monetary policy is impacting the U.S. M&A market. Therefore, I present the following research question:

"How does U.S. monetary policy impact the U.S. M&A market?"

Because of the aggressive monetary policy and the more active M&A market compared to Europe, I choose to limit my research to the U.S. (Refinitiv, 2022). I will try to answer this question by looking at the impact of interest rates on 3 different areas of M&A. First, I examine the relationship between interest rates and acquirer debt at the moment of takeover, in light of divergent findings in prior research. Then I will investigate the relationship between interest rates and target multiples, which was previously found to be negative by Horn & Fischer (2021) and Ubl & Brett (2014). Lastly, I research the relationship between interest rates and acquirer performance, which were found to be negatively related with each other by Adra et al. (2020).

Through this, I aim to gather insight into the drivers for M&A valuations. Furthermore, it might help in forming expectations about the future M&A climate in terms of debt use and acquirer return. I will also provide possible explanations for the findings in this research based on economic theory. The remainder of this paper is structured as follows. In the next section I will present the theoretical framework behind the M&A market, and the hypotheses to my sub-questions based on the relevant literature. Then, I will describe the dataset and discuss the methodology of my research. Afterwards, I will look at the results and give an interpretation in my discussion. Finally, I will conclude with a summary of my findings, a discussion of the limitations and provide recommendations for further research.

2. Theoretical Framework

2.1 Debt

A company's motivation for the extent of their leverage use might have more than one explanation. Well known theories on corporate debt are for instance the pecking order theory, which describes that companies will always exert a preference for internal funds such as cash, rather than external funds such as debt (Shyam-Sunder & Myers, 1999). Another well known theory on corporate debt is the static tradeoff theory, which predicts that firms will tradeoff the tax benefits against the financial distress costs of extra leverage to arrive at an optimal amount of debt (Myers, 1984). However, these theories are all discuss leverage use in a more general corporate sense, rather than within the context of M&A specifically.

One paper that did research on this topic within M&A, is the one by Adra et al. from 2020. In their paper, the authors show that a rise in the Federal Funds Rate (FFR) is associated with an increase in the cost of debt as well as the indebtedness of the acquirer, which they define as Debt/Equity (Adra, Barbopoulos, & Saunders, 2020). This is quite an interesting finding, considering that this goes directly against the so-called Interest Rate Effect. The Interest Rate Effect describes that as the Federal Reserve increases interest rates, it will be more expensive to borrow, which will induce fewer people to do so (Baldwin, 2022). Thus, one would assume it to be likely to also observe this phenomenon in the M&A market.

The authors explain their finding through the expected financing cost channel. According to the expected financing cost channel, monetary tightening increases the cost of financing, which reduces viability of corporate investments. It predicts that tight monetary policy produces future challenges for merging firms. Given that M&As exhaust significant financial resources, post-acquisition financing of future business operations becomes highly dependent on external financing. Therefore, the channel predicts that in contractionary monetary environments, M&A announcements tend to be negatively perceived by equity investors, especially when acquirers are financially constrained at the time of the announcement. This causes acquirers to experience an increase in their post-acquisition financing costs, a reduction in their cash reserves and an overall decline in their shareholder wealth which must be funded by an increase in debt. This is an interesting finding considering that it clashes with the traditional interest rate effect as described by Baldwin. There are, however, some important sidenotes to be made regarding their research.

Adra et al. use the federal funds rate (FFR) as a proxy for monetary policy and study its impact on the use of debt in mergers and acquisitions among other dependent variables. So, what does this FFR entail? The FFR refers to the target interest rate set by the Federal Open Market Committee (FOMC). In essence, this target is the rate at which commercial banks borrow and lend their excess reserves to each other overnight (Forbes, 2022). Although this might seem like an adequate proxy for monetary policy, there is one big shortcoming in using this metric as an explanatory variable. Because it has a lower bound of zero, it does not convey information about monetary policy below this bound (Wu & Xia, 2016).

Although the FFR has provided the basis for most empirical studies on the interaction between monetary policy and the economy, the recent years of quantitative easing (QE) have caused the FFR to hover around zero for quite some time as of writing. QE is a form of expansionary monetary policy in which a central bank purchases securities on the open market to reduce interest rates and increase the money supply. It is most often used when nominal interest rates hover around the zero lower bound and economic growth is stalled (Rogoff, 2017). In that case, central banks do not have many tools left to stimulate economic growth, so they turn to quantitative easing. Because of this, the FFR has ceased to provide an adequate proxy of monetary policy, which causes one to question the validity of the research by Adra et al. In this research, I try to work around this by using the Wu-Xia (WX) shadow rate.

The WX shadow rate is a concept that was introduced by Wu & Xia in their 2016 paper on measuring the impact of monetary policy at the zero lower bound. Their research builds upon the research by Black (1995) who first proposed the concept of a shadow rate. In his paper, he looks at interest rates as options, and states that since people have the option to hold currency at a zero nominal interest rate, the nominal short rate cannot be negative. The shadow rate represents what the short rate would be without the currency option, thus allowing it to go below the zero lower bound.

However, there only exists an analytical solution to this model in a one-factor model. Wu and Xia build upon this notion by proposing a simple analytical representation for bond prices in a multifactor shadow rate term structure model and demonstrate that their model offers an excellent empirical description of the recent behavior of interest rates compared to the previously used Gaussian affine term structure model. More importantly, Wu & Xia show that the shadow rates calculated by their model exhibit correlations with macro variables of interest in the period since 2009, as the federal funds rate did in data prior to the Great Recession. This makes it a convenient measure of interest rates as it also factors in unconventional monetary policy. So now that I have defined an adequate proxy for monetary policy, what empirical evidence can we expect to find regarding the impact of the WX rate on the use of debt? However, it is difficult to draw any conclusions on this impact in advance. Because this measure has only been developed recently, the number of studies using the WX rate is limited, and within M&A even non-existent, thereby underlining the importance of this study even further.

One study that does not necessarily use the WX rate, but does talk about the impact of quantitative easing in the context of M&A is the one by Acharya et al. (2022). According to the authors, investors exposed to QE drive the demand for downgrade-vulnerable investment grade corporate bonds called prospective fallen angels. These prospective fallen angels meet the QE-induced demand by supplying bonds largely for the purpose of financing risky acquisitions. Prospective fallen angels can defer downgrades through M&A deals, as the immediate risk of being downgraded to high yield is minimal for those who engage in such transactions. In other words, according to Acharya et al, lower interest rates due to quantitative easing should increase acquirer debt, which is in line with the traditional interest rate effect.

One study that looks at the impact of interest rates on investment and debt in a more general sense is the one by Chystiakova (2016). They used the WX rate to study the impact of interest rates on investment and debt in a more general sense and had findings in line with Adra et al, stating that the contractionary policy also had a positive impact on the use of corporate leverage. Her explanation for this was not related to debt but to the numerator of her definition of leverage, the market capitalization. According to her, a higher cost of external finance leads to a lower capital investment and thus a negative impact on the asset's price, thus lowering the denominator (market cap) and increasing the measure for leverage.

Using a balance-sheet item such as equity or market cap rather than a P&L item such as EBITDA makes it more difficult to study the impact of interest rates on the use of debt. This holds true because interest rates should not impact EBITDA since it does not take interest expenses into account, whereas interest rates do often impact asset prices, thus making them less fit as measures of leverage (Bordo & Landon-Lane, 2013). Therefore, I use Debt/EBITDA multiples as proxies for leverage rather than Debt/Equity or Debt/Market Cap.

Because interest rates should not impact the EBITDA, but should impact debt based on the findings by Baldwin (2022) regarding the interest rate effect, it seems plausible to expect a negative relationship between debt and interest rates. Considering this supplemented by the evidence provided by Acharya et al. (2022), I present the following hypothesis to my first sub-question:

H1: *"Interest rates have a negative relation with the relative amount of debt used by acquirers in U.S. M&A transactions"*

2.2 Multiples

To get a clear overview of the impact of monetary policy on the state of the M&A market as a whole, we must first establish what defines the state of the M&A market. In M&A reports, a certain total deal *value* in a certain period is often used as substantiation for stating that the M&A market is "booming" (Deloitte, 2021). However, this is a difficult measure to use when drawing comparisons. For instance, if you try to compare total deal value between sectors, it is a bit of an apples and oranges-comparison because one sector might have a larger market size than the other, which will most likely result in a larger yearly deal value within that sector, even in the absence of a booming M&A market. The same report also discusses a high deal *volume* within a certain period when describing a booming M&A market. However, when looking at deal volume across regions, it is easy to see that it's likely that this measure is also related to the physical size of a region, thus making it difficult to use it for comparisons in future research (PWC, 2022). Another measure that is discussed in the report by Deloitte when referring to booming M&A markets are high EBITDA multiples paid by acquirers within a certain sector[1]. In contrast to the previous two measures, this one ís comparable across countries and sectors. So how does monetary policy impact multiples? To find the answer to this question, we first have to understand why we use certain multiples to value certain companies.

2.2.1 Valuation

There are many things one can refer to when discussing the "value" of a company, for instance, the value of its cash, its equity, or its enterprise value. That last measure is the one that is most often used when discussing the value of a company in the form of Enterprise Value over EBTIDA. A company's Enterprise Value (EV) is equal to its market capitalization plus the market value of its debt, minus cash, and cash equivalents and can be thought of as the effective cost of buying a company and represents the sum of all claims by all claimants, so both debt holders as well as equity holders. It can be seen as a loose proxy for cash flow which is useful in cases where you want to draw comparisons in the value of companies between sectors with large and small capital expenditures. Furthermore, EBITDA also does not take taxes into account which allows for transnational comparisons because it ignores the distorting effects of individual countries' taxation policies. Because of the properties of both measures mentioned above, the EV/EBITDA multiple is the measure that is used most often by M&A advisories to value companies and compare those values to other companies (Shaffer, 2022).

This is the case because it is a better reflection of a company's true value than measures such as Price/Earnings which could easily be distorted. For instance, in times of contractionary monetary policy, increased financing costs could negatively impact earnings, thus increasing the valuation (P/E ratio) of a company due to a lower denominator, merely by negatively impacting net income. An important side note though is that EV multiples can vary a lot between sectors (Chan & Lui, 2010). Therefore, it is important to differentiate between industries when conducting research on multiples.

2.2.2. Monetary Policy & Valuations

How does monetary policy impact valuation? The impact of monetary policy on asset prices has been studied thoroughly. Bernanke & Kuttner (2005) found that on average, a cut in the Federal

[1] With EBITDA multiple, we refer to the Enterprise Value divided by the EBITDA

funds' target rate is associated with an increase in broad stock indices. Rosa (2012) found that large-scale asset purchases and Federal funds target rate cuts both have the same effect. Rigobon & Sack (2004) found that the same was true the other way around and that short-term rate hikes cause a decline in stock prices. One paper that looks at the impact of unconventional monetary policies such as QE on valuation is the one by Lacalle (2018) who argues that loose monetary policy has generated unquestionable and disproportionate financial asset inflation. The general academic consensus seems to be that lower interest rates have caused an increase in multiple valuations.

However, it is important to note that the aforementioned papers all look at the impact of monetary policy on financial markets in general, and not in the context of mergers and acquisitions specifically. Financial markets are in part driven by emotion, and investors tend to overreact to news, which might cause valuations to increase firmly on paper due to inflated asset prices (Mahani & Poteshman, 2008). Therefore, it is interesting to investigate whether this effect also holds true in the context of mergers and acquisitions, considering that this concerns asset purchases by larger parties such as private equity investors or corporations, rather than individual investors. Furthermore, the purchasing of a company is a lengthy process which takes on average four to five months to close, thus making the explanation of overreacting to news unlikely (Gatti, 2017). When investigating the academic body of research available, one study that mentions the relationship between monetary policy and firm valuations in the context of M&A this is the one by Horn and Fisher (2021). They find that a contractionary monetary policy shock worsens firm valuations. A paper contradicting the findings by Horn and Fisher is the one by Ubl and Brett (2014), who do not find a relationship between the average EBITDA multiple and monetary policy. In a more general sense, Ubl & Brett state in their paper that monetary policy theory suggests that negative shocks to monetary policy that lowers interest rates should increase asset prices. This should hold true because a lower interest rate decreases the cost of borrowing, which should increase investment and thus raise asset prices levels. Bromley & Zhou (2011) found that lower interest rates actually cause lower valuations, which goes directly against the theory of monetary policy that is discussed by Ubl & Brett. However, an important side note is that the research conducted by Bromley and Zhou only uses 375 observations, which makes the validity of the research a bit questionable.

Although there exists an extensive body of research on both monetary policy and M&A separately, the interface between these two fields of study appears to be understudied. Based on the previous empirical evidence discussed above and the prediction of monetary policy theory, I pose the following hypothesis to my second sub-question:

H2: *"Interest rates have a negative relation with EV/EBITDA multiple valuations that are paid by acquirers in U.S. M&A transactions"*

2.3 Performance

The last aspect of the M&A market that I will investigate in this paper is the impact of monetary policy on M&A performance. But then the question arises: what is M&A performance?

2.3.1 Defining M&A Performance

Although this might seem intuitive at first, there are many ways to measure M&A performance. For instance, in the paper by Adra et al. (2020) the authors use the Acquirer CAR (cumulative abnormal returns) and the $\Delta Acquirer\_RoA$ (return on assets) as measures of M&A performance. They define Acquirer CAR as the cumulative return in excess of the expected return according to the Fama & French 3-factor model, in the 5 days surrounding the announcement, which translates to $\sum_{-2}^{+2} AR_{i,t}$ in mathematical terms (Fama & French, 1993). Considering that this only looks at the returns around the announcement of the acquisition, this measure can be seen best as an ex-ante expectation of the transaction by the market, rather than a realized measure of performance (Zollo & Meier, 2008). According to Zollo & Meier, considering the widespread evidence of market imperfections to the announcement of acquisition events, the use of long-term windows is not only warranted, but even preferred over the more diffused short-window alternatives within corporate finance literature. I will discuss their paper more thoroughly later on, but first I will look at Adra et al.'s second measure of M&A performance: $\Delta Acquirer\_RoA$.

In their paper, the authors define $\Delta Acquirer\_RoA$ as a second measure of acquirer performance. This measure translates to the difference in the acquirers return on assets between the years before and after a takeover, which might seem like a decent way of quantifying the long-term performance of an acquisition. However, it is important to note that this measure concerns all assets of the acquiring company. Therefore, as companies get bigger in terms of assets, it is likely that the acquisition itself has a smaller impact on the difference in a company's RoA, which makes this measure to biased to use in research. Since both performance measures used by Adra et al. do not really suffice as adequate measures of M&A performance, we look a bit further into the work by Zollo & Meier (2008).

As I previously stated, the authors argue that short-term performance measures such as event studies using the 5-day Acquirer CAR around the announcement of the transaction are more of a collective expectation by the financial market of the transaction, rather than a realized performance measure. Longer-term performance measures on the other hand can be seen as an ex-post realization of both transaction-level as well as firm-level benefits. Zollo & Meier developed a model with several measures relating to several different aspects of a takeover, such as the integration process, accounting performance and customer retention. In their paper, the authors conclude that M&A performance is a multifaceted construct and therefore recommend that future researchers of this subject should use a combination of objective and subjective measures if possible. However, datasets with subjective measures of acquisition performance are very difficult to find and do not lie within my disposal.

Nonetheless, in the results section of Zollo & Meier, the authors show a significant link between the measure of long-term financial performance and overall acquisition performance. Thus, I can proxy overall acquisition performance by using the financial measure presented in the paper by Zollo & Meier. This metric is defined as the cumulative monthly returns of the acquirer over 36 months versus a benchmark of companies of a similar size in a similar industry located in the same geographic region. However, the dataset by Refinitiv Eikon only provides stock data on the acquiring company at most 180 days after the acquisition, which still suffices as a medium-term performance measure, considering the academic body of work supporting this (Gates & Very, 2003; King, Dalton, Daily, & Covin, 2004). In mathematical terms, this translates to: $\sum_{t-1}^{t+180}(R_{i,t} - R_{m,t})$ where R_i is the return of stock i at time t, and R_M is the return of the relevant benchmark at time t.

2.3.2 Impact of Monetary Policy on Performance

So how do we expect this measure to be impacted by monetary policy? As previously discussed, according to the interest rate effect, expansionary monetary policy should increase the availability of money, and therefore increase investment. This, in turn, could drive up stock prices, and since the proxy is based on stock prices, it's reasonable to assume that low interest rates could improve M&A performance. However, the increased flow of money into the stock market due to low rates is systemic, meaning that the market as a whole should experience higher pricing, which will be reflected in higher benchmark returns as well and therefore will not have an impact on our metric, considering it uses returns in excess of the market. This is a reason why using abnormal returns - rather than gross returns - is a good way to differentiate between the impact of the merger and general market sentiment.

However, this is yet to provide us with an expectation on the impact of monetary policy on M&A performance. Upon further examination of possible explanations from prior research, it becomes apparent that there are multiple perspectives on explaining the impact of monetary policy on M&A performance. I present two channels through which monetary policy can influence M&A performance.

2.3.3 Channel 1: Buyer Cautiousness

As Gaughan (2009) notes, shareholders of well-financed buyers benefit by being able to acquire targets at attractive prices. Gaughan also notes that shareholders may also benefit from buyers being more cautious about making deals. So, when are buyers more cautious about making deals? Adra et al. showed in their 2020 paper that a rise in the FFR predicts a higher likelihood of deal withdrawal due to raised concerns about future financing. Based on these findings, can we conclude that contractionary monetary policy makes buyers more cautious, thus increasing the acquirer CAR across a population? Well almost. Buyer cautiousness is not the only channel through which monetary policy can influence M&A performance.

2.3.4 Channel 2: Increased Financing Costs

It is important to remember that Adra et al. also shows that higher rates raise financing costs and decrease acquirer CAR. Performance must therefore also be influenced by financing costs, which should show the negative impact of contractionary monetary policy on acquirer CAR. However, either one of these effects must have a larger impact than the other, in which case we will observe either a negative or positive impact. If both effects are equally as strong, they might cancel each other out, thus leaving us with observing no impact of monetary policy on returns.

Because Adra et al. only investigate short-term acquirer returns, and the empirical evidence on the impact of monetary policy on medium-term returns is quite lacking, it is rather difficult to draw conclusions in advance about whether the impact of monetary policy on returns will be either positive, negative or zero. However, the cautiousness channel only shows that companies become more cautious in acquiring companies, not inherently better at picking the right ones. Therefore, I think that financing costs will have a larger impact and that we will see findings in line with those by Adra et al. in the medium term as well. Based on this, I present the hypothesis to my third and final sub-question:

H3: *"Monetary contraction is associated with lower acquirer performance in U.S. M&A transactions"*

When studying the impact of one variable on another, it is important to beware of endogeneity problems. Endogeneity occurs when a predictor variable in a regression model is correlated with the error term. Considering that it seems highly unlikely that a single corporation's stock movement would have an impact on the Federal Reserve's monetary policy, we can disregard possible endogeneity problems arising from simultaneity bias. Omitted variable bias in this context would mean that there are other factors impacting the acquirer performance than just the interest rate that are not included in the regression. Because we use stock returns as a proxy for acquirer performance, there might be several factors that impact stock returns other than just interest rates. However, for bias to arise, the omitted variable must be correlated with both the dependent variable as well as one or more explanatory variables. In the next section, we will take a look at factors that might possibly influence stock returns.

2.3.5 Factors Impacting Stock Returns

There exists a large body of work on the determinants of stock returns. One of the most important theories in finance is called the capital asset pricing model (CAPM) which was first introduced by Treynor in his paper on market value, time and risk (Treynor, 1961). In essence, the CAPM model shows how the market must price securities in relation to their security risk class. In 1993, Eugene Fama and Kenneth French introduced the three-factor model which builds upon the

CAPM by also including a size and value premium. These premiums were based on the fact that small-cap firms and companies with a high book-to-market ratio tend to outperform the returns predicted by the CAPM. The 3-factor model explains more than 90% of diversified portfolio returns (Basiewicz & Auret, 2010). This model was later extended by the authors to the 5-factor model, which also included profitability and investment factors (Fama & French, 2015). Although all the factors described above might impact stock returns, it is highly unlikely that these factors also impact interest rates, considering that these are determined by the US Federal Reserve who base their decisions on the general state of the economy rather than individual company characteristics. Therefore, I believe that the possibility of endogeneity bias arising from the factors described above is very limited. Because I am researching the impact of interest rates on acquirer performance rather than aiming to predict acquirer returns, I choose not to include these factors in my regression.

A factor that might have an impact on both the acquirer performance as well as the interest rate is the GDP growth. In his paper on economic growth and equity returns, Ritter (2005) finds a negative correlation between the per capita GDP growth and real stock returns. Although the relationship between GDP growth and interest rates has been less widely studied within the United States, there is some evidence of the existence of this relationship in countries such as Kenya or Nigeria (Harmon, 2012; Udoka & Anyingang, 2012). Therefore, it seems warranted to investigate the possible role that GDP growth plays. Furthermore, I add in the inflation and unemployment rates as macro-economic control variables to reduce noise and decrease standard errors.

3. Data

In this section, we will first discuss the validity of the databases I use to conduct the empirical part of my research. Then I will discuss possible biases that might arise when conducting my research. Afterwards, I will discuss the methodology I used to prepare the dataset, and lastly, I will take a look at some descriptive statistics of the dataset.

3.1 Monetary Policy Data

As I discussed in the theoretical framework, I will be using the Wu-Xia shadow rate as a proxy for monetary policy, due to its representation of the impacts of monetary policy below the zero lower bound. The figures for this shadow rate are posted on the website of the Atlanta Federal Reserve for free and provide data from 1990 until 2022.

3.2 M&A Data

To gather data on mergers and acquisitions, I used the Eikon Deals Dataset. This is a dataset provided by Refinitiv that provides coverage of global M&A activity providing coverage of over 1.3 million deals in total. I was able to access this database for free through the digital Eikon Datastream machines that were provided by the EUR. Since I am looking to study only the U.S. M&A market, I refined my search to only include completed U.S. deals. Because I only had data on the Wu-Xia Shadow Rate from 1990 onwards, I further refined my search to only include deals from 01-01-1990 until 25-01-2022, which was the last available deal. Lastly, I refined my search to include only listed acquirers. This was necessary because I needed stock information for my research question on acquirer performance. Furthermore, in order to answer my other sub-questions I had to have data on balance sheet items such as debt, or P&L items such as EBITDA. Because U.S. public companies are required by the SEC to publish information like this, it was most efficient to limit my research to public companies. These search restrictions left me with 6204 observations in total.

3.3 Benchmark Data

In order to provide the most accurate benchmarks possible, I calculate abnormal returns using benchmark data specific to industry and region. Our dataset differentiates between 12 different acquirer macro industries, so I matched each industry to the appropriate benchmarks, displayed in Table 1. In order to provide the most accurate benchmarks possible, I calculate abnormal returns using benchmark data specific to industry and region. Our dataset differentiates between 12 different acquirer macro industries, so I matched each industry to the appropriate benchmarks, displayed in Table 1.

Acquirer Macro Industry	Benchmark
Consumer Products and Services	iShares U.S. Consumer Discretionary ETF
Consumer Staples	iShares U.S. Consumer Staples ETF
Energy and Power	iShares U.S. Energy ETF
Financials	iShares U.S. Financials ETF
Healthcare	iShares U.S. Healthcare ETF
High Technology	iShares U.S. Technology ETF
Industrials	iShares U.S. Industrials ETF
Materials	iShares U.S. Basic Materials ETF
Media and Entertainment	Invesco Dynamic Leisure & Entertainment ETF
Real Estate	iShares U.S. Real Estate ETF
Retail	VanEck Retail ETF
Telecommunications	iShares U.S. Telecommunications ETF

Table 1: Acquirer macro industries and corresponding benchmarks

To gather pricing data on these benchmarks I used Yahoo Finance and downloaded all available pricing data. However, industry-specific ETFs have only been around for approximately the last 25 years, so we only have pricing data on industry-specific benchmarks starting around the turn of the century. Next to that, there is an important sidenote to make that has not been mentioned in any of the previous research on M&A performance using benchmark returns. That is, the fact that some of the acquirers completing the takeover are part of the benchmark that is used to calculate abnormal returns, thereby causing a bias in the calculation of abnormal returns. To put this into perspective, let's look at the following situation where an acquisition is very successful, and the acquiring company A has a buy-and-hold CAR of 30% over the 180-day period after the takeover announcement. If the acquiring company has a substantial market capitalization, it is likely to also be a constituent of the benchmark index that is used to calculate abnormal returns. Because company A is partly responsible for the returns of the benchmark, if we were to include company A's double-digit returns into the benchmark, we'd be counting the returns by company A twice, thereby biasing the abnormal return we are trying to calculate. In order to correct for this, we have to adjust the benchmark returns to what they would have been, had company A not been a constituent. In order to do so, I used the Eikon ETF database by Refinitiv to gather data on the constituents of all the ETFs in Table 1. Because this database only provides data from 2007 onwards, we can only correct acquirer returns for constituent weightings for deals after 2007. So how do I adjust these returns? In order to arrive at a benchmark return that does not include the returns of the acquirer, we make an adjustment represented in formula 5.

$$r_{benchmark,adj} = \frac{r_{benchmark} - (r_{acquirer} * w_{acquirer})}{1 - w_{acquirer}} \qquad (5)$$

Although this all might seem like a storm in a teacup at first glance, when further investigating our dataset, we see that it includes acquiring companies such as ExxonMobil which had a weighting of more than 24% in the relevant benchmark at the time of takeover. This translated to a change in benchmark return from -2% before adjusting, to +2% after adjusting. Therefore, examples such as this justify omitting a part of my dataset in order to get less biased returns. This leaves us with 1620 deal observations to investigate performance.

3.4 Macro-economic control variable data

To supplement my dataset, I use the following macro-economic control variables: inflation, unemployment, and GDP growth. The monthly data on the U.S. inflation rate was gathered through the St. Louis Federal Reserve. The data on the U.S. unemployment rate is gathered through the U.S. Bureau of Labour Statistics. The annual data on the U.S. GDP growth was gathered through the World Bank Group. I then matched these datasets to the relevant years of the deals.

3.5 Preparation

The dataset provided by Eikon already had information on the convertible debt and the straight debt of the acquirer at the time of the takeover. I added those two numbers to arrive at the acquirer's total debt at the time of takeover. Then I divided this number of total debt by the company's last 12 months EBITDA to get to my measure of leverage. However, there is an important problem that arises when using Debt/EBITDA multiples as a measure of acquirer leverage. As a company's EBITDA gets more negative, the debt ratio will get closer to zero, thus giving the illusion that the company is less levered, while it is actually more levered, considering that it has taken on debt while operating at a negative EBITDA. This problem might also arise when researching EV/EBITDA multiples paid for the target. Thus, the ratios of debt to EBITDA and enterprise value to EBITDA are non-monotonic relationships and might bias my research. Because the companies in the dataset are in the position of acquiring another company, most companies have a positive EBITDA. Therefore, omitting all deals where the acquiring company has a negative EBITDA has a limited impact on the sample size, leaving us with 5245 observations for debt multiples, and 6204 observations for the enterprise value multiples. The dataset provided by Eikon already had information on the convertible debt and the straight debt of the acquirer at the time of the takeover. I added those two numbers to arrive at the acquirer's total debt at the time of takeover. Then I divided this number of total debt by the company's last 12 months EBITDA to get to my measure of leverage. However, there is an important problem that arises when using Debt/EBITDA multiples as a measure of acquirer leverage. As a company's EBITDA gets more negative, the debt ratio will get closer to zero, thus giving the illusion that the company is less levered, while it is actually more levered, considering that it has taken on debt while operating at a negative EBITDA. This problem might also arise when researching EV/EBITDA multiples paid for the target. Thus, the ratios of debt to EBITDA and enterprise value to EBITDA are non-monotonic relationships and might bias my research. Because the companies in the dataset are in the position of acquiring another company, most companies have a positive EBITDA. Therefore, omitting all deals where the acquiring company has a negative EBITDA has a limited impact on the sample size, leaving us with 5245 observations for debt multiples, and 6204 observations for the enterprise value multiples.

The dataset also provided data on the target's Enterprise Value/EBITDA multiple for most deals. According to Eikon, this measure was calculated by multiplying the number of actual target shares outstanding from its most recent balance sheet by the offer price and then adding the cost to acquire convertible securities, plus short-term debt, straight debt and preferred equity minus cash and marketable securities. The target's EBITDA is earnings before interest, taxes, depreciation and amortization for the 12 months ending on the date of the most current financial information prior to the announcement of the transaction.

For the third sub-question, the database provided information on the stock price one day before announcement and 180 days after announcement which allowed me to calculate the acquirer returns during that period. Then I used the announcement date to find the stock price data for the corresponding industry benchmark and used that to calculate stock returns for the benchmark. Then I adjusted the benchmark returns if the acquiring company was a constituent as I described in the beginning of this chapter.

To get the relevant interest rate for investigating my sub-questions on debt and multiples, I looked at the WX rate at the time of the takeover announcement. To answer my sub-question on performance, I looked at the average WX rate during the period one day before and 180 days after announcement of the transaction. The dataset had a lot of outliers so in order to account for those, I Winsorized the dataset at the 95 percentile. All the descriptive statistics displayed in the tables are those of the Winsorized data.

3.6 Descriptive Statistics

In Table 2 we can see some descriptive statistics on our debt multiple data. We can see that most industries have approximately the same number of observations, but that the financial and technology sectors have a higher number of observations. The mean number of debt of our entire sample lies around 3.2. We can see that most industries have mean debt numbers that lie close to this number, with real estate being a bit of an outlier with a mean debt multiple of more than 11. When looking at the maximum values for debt multiples we see that there might exist some outliers in the dataset, which I'll deal with in the methodology section of the paper.

Acquirer Macro Industry	Observations	Mean	Median	σ	Min	Max
Consumer Products and Services	230	1.426	0.972	1.667	0	10.066
Consumer Staples	190	2.039	1.498	1.784	0	8.698
Energy and Power	507	2.885	2.353	2.382	0	10.066
Financials	1489	3.126	1.864	3.201	0	10.066
Healthcare	437	1.841	1.160	2.155	0	10.066
High Technology	814	1.151	0.343	1.879	0	10.066
Industrials	520	1.821	1.270	1.925	0	10.066
Materials	268	2.132	1.632	2.188	0	10.066
Media and Entertainment	269	2.990	2.504	2.633	0	10.066
Real Estate	188	6.034	5.948	3.242	0	10.066
Retail	151	1.594	1.237	1.611	0	10.066

Telecommunications	182	1.989	1.378	2.186	0	10.066

Table 2: Descriptive statistics: winsorized acquirer debt multiples

In Table 3 (see appendix), we can see some descriptive statistics on our enterprise value multiple data. Once again, the financial and technology sectors are a bit overrepresented in this sample. The mean EV multiple of the entire sample lies around 51. The mean EV multiples per sector are dispersed ranging from means of 14 in Energy & Power to 100 in healthcare. These numbers seem very high considering that most sector multiples in M&A reports lie around 10 to 15 (NYU Stern, 2021). A possible explanation could be found when examining the maximum values in our sample, which go up to more than 33 thousand in some sectors. Large EV multiples such as these could be explained by acquirers justifying large purchase prices through things such as a high expectation of earnings growth in the target company.

In Table 4 (see appendix) we can see the descriptive statistics for our sample on acquirer performance in excess of an industry specific benchmark. We can see that the measn acquirer performance is positive in all sectors, with especially high means in the healthcare sector. We observe that the maximum values are extremely high which might cause the mean to be skewed. There might exist some outliers in the multiple datasets as well. I deal with these outliers by winsorizing the dataset which I describe in the methodology part. The winsorized dataset is plotted in Table 5 (see appendix).

In Table 6 (see appendix), we see the descriptive statistics for the Wu-Xia shadow rate at the time of deal announcement for all 6204 observations in the dataset. The mean shadow rate lies around 3.32% with a standard deviation of approximately 2.56%. The lowest observed point of the shadow rate is 2.98% and the highest rate observed during a deal was 8.1%. The descriptive statistics for the average shadow rate during the 180-day holding period lie around the same points.

In Table 7 (see appendix), we see the descriptive statistics for the macro-economic control variables. We can see that the mean inflation rate lied around 4%, the mean GDP growth was approximately 2% and that the unemployment rate was ~5.5%.

4. Methodology

In this section, I will discuss the empirical models used to reveal evidence used to answer my sub-questions.

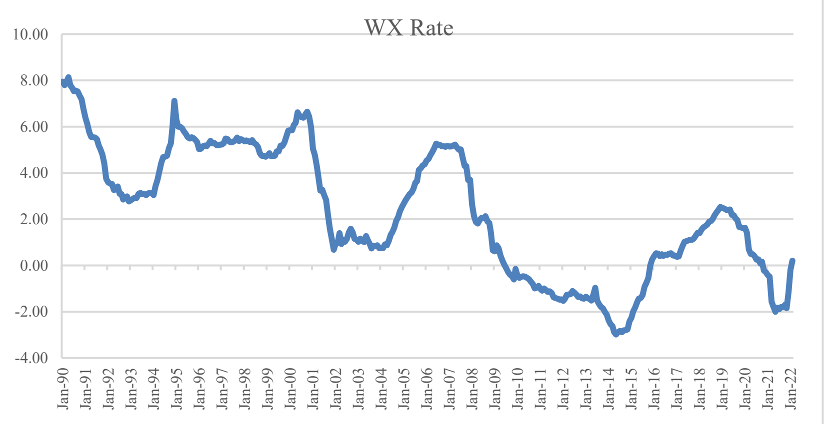

Figure 1: Line graph of the WX rate in the period 1990 - 2022

4.1 Monetary Policy & Debt

To answer my sub-question on the impact of monetary policy on the use of debt by acquirers in mergers and acquisitions, I run a linear regression with my relative debt measure as a dependent variable. I use the WX rate as a proxy for monetary policy, which is my main explanatory variable of interest called. To answer my sub-question on the impact of monetary policy on the use of debt by acquirers in mergers and acquisitions, I run a linear regression with my relative debt measure as a dependent variable. I use the WX rate as a proxy for monetary policy, which is my main explanatory variable of interest called *WX at Takeover*. Furthermore, I include the industry in which the acquirer is active as a dummy variable. When we look at figure 1, we can see a clear trend in the WX rate over the years. However, I do not include a trend term in the regression analysis because this trend should already be encapsulated by the inclusion of the WX rate in the regression. The model is specified in regression 1.

$$Regression\ 1: Debt/EBITDA_{i,t} = \beta_1 WX_t + \beta_2 GDP\ Growth_t + \beta_3 Inflation_t + \beta_4 Unemployment_t + \beta_5 LN\ Acquirer\ Net\ Assets + \beta_6 Acquirer\ Net\ Sales + \beta_7 Industry + e_{i,t}$$

In this model, β_1 measures the influence of the WX shadow rate at time t of the acquisition, on the amount of relative debt used in the acquisition at time t by the acquiring firm i. I run the model at firm level with industry fixed effects. Because of the empirical evidence supporting the pecking order theory, we can assume that a firm's internal preference for cash over debt and debt over equity stays constant (Shyam-Sunder & Myers, 1999). This in combination with the use of a debt measure relative to EBITDA takes away possible impact of a company's size on the relative debt. Furthermore β_2, β_3 and β_4 describe the impact of the macro-economic control variables on relative debt at time t of the acquisition. Lastly, β_5 and β_6 describe the impact of firm specific control variables which are the natural logarithms of the acquiring firm's Net Assets and Net Sales in the year of the acquisition.

As stated in the Data section, considering that some of the extreme values in the dataset are more than 300 times as high as the median, there might exist some outliers in the dataset. To deal with these outliers, I use robust MM regressors. In addition to using only the observations with positive EBITDA, we also regress using the entire dataset as a robustness check. The results of this check are displayed in the appendix.

4.2 Monetary Policy & Valuations

In order to find an answer to the second sub-question on the relationship between monetary policy and M&A valuations, I also ran the linear regression specified in regression 2.

$$Regression\ 2: EV/EBITDA_{i,t} = \beta_1\ WX_t + \beta_2 GDP\ Growth_t + \beta_3 Inflation_t + \beta_4 Unemployment_t + \beta_5 LN\ Acquirer\ Net\ Assets + \beta_6 Acquirer\ Net\ Sales + \beta_7 Industry + e_{i,t}$$

In this model, β_1 measures the influence of the WX shadow rate at the time of the takeover on the valuation of the target company. I run the model at firm level with industry fixed effects. Furthermore, β_2, β_3 and β_4 describe the impact of the macro-economic control variables on the target valuation at time t of the acquisition. Lastly, β_5 and β_6 describe the impact of firm specific control variables which are the natural logarithms of the acquiring firm's Net Assets and Net Sales in the year of the acquisition.

For the analysis of this second sub-question, I use a similar methodology to the methodology of the first sub-question. When observing the descriptive statistics displayed in Table 3, it becomes clear that there exist outliers in the dataset. For this sub-question, I also deal with outliers by using robust MM regressors.

4.3 Monetary Policy & Performance

Lastly, to answer my third sub-question, I ran a linear regression using the acquirer's 180-day buy-and-hold returns as the dependent variable. The average WX rate over the 180-day holding period is used as an explanatory variable combined with the industry in which the acquirer is active. The model is specified in regression 3.

$$Regression\ 3: Abnormal\ Return_{i,t-1;t+180} = \beta_1 WX_{t-1;\,t+180} + \beta_2 GDP\ Growth_t + \beta_3 Inflation_t + \beta_4 Unemployment_t + \beta_5 LN\ Acquirer\ Net\ Assets + \beta_6 Acquirer\ Net\ Sales + \beta_7 Industry + e_{i,t}$$

In this model, β_1 measures the influence of the average shadow rate during the period in the day before acquisition announcement and 180 days thereafter on the abnormal acquirer return during that period. Furthermore β_2, β_3 and β_4 describe the impact of the macro-economic control variables on the acquirer abnormal return from time t-1 to t+180 relative to the acquisition announcement. Lastly, β_5 and β_6 describe the impact of firm specific control variables which are the natural logarithms of the acquiring firm's Net Assets and Net Sales in the year of the acquisition.

I run the model at firm level with industry fixed effects. Like the methodology of the first two sub-questions, I start off by generating a scatterplot of the abnormal return over the years. Once again, we see that some observations have a very high abnormal return. To correct for this, I remove the outliers by winsorizing the dataset, since MM regressors do not provide to be an adequate solution.=. I run the regression again using regular OLS and the winsorized set of abnormal return data and test for heteroskedasticity. Then I test the other assumptions of the CLRM.

As I discussed in the theoretical framework, we have to be careful of endogeneity problems. If we leave out a variable influencing both the dependent as well as the explanatory variable, the regression results might be biased due to omitted variable bias. Based on previous empirical findings, I suspected GDP growth to be an endogenous regressor. An endogenous regressor is one that is correlated with, or has non-zero covariance with the error term of the equation. In order to verify whether GDP growth was an endogenous regressor, I ran the regression and predicted the residuals and tested the correlation between GDP growth and the error term (see Table 5). Because there was no serious correlation between GDP growth and the error term, I concluded that GDP growth was not an endogenous variable.

Another possible issue was the empirical evidence of a relationship between GDP growth and interest rates, which could possibly cause multicollinearity problems in the model. In order to establish whether there exists a multicollinearity problem I check the variance inflation factor for each coefficient. I find that both the variance inflation factors for both WX rate as well as GDP growth are very close to 1. Therefore, we can establish that the multicollinearity problem in the regression is very small and that we do not have to take it into account when interpreting the results.

5. Results

In this section I will discuss the results of the analysis discussed above. In short, I find that the WX rate has a negative relation with acquirer debt and acquirer performance, but a positive relation with the target multiples. In the rest of this section, I will discuss the results with regard to my sub-question on interest rates and debt. Then I will discuss the findings with regard to the sub-question on interest rates and multiples and lastly, I will discuss the findings related to the sub-question on interest rates and performance.

5.1 Findings Debt

In Table 8 we can see the results of the robust regression with relative debt as a dependent variable and the WX rate at takeover and the acquirer industry as explanatory variables.

	$Debt/EBITDA_{i,t}$
WX_t	-9.850***
	(1.089)
$Inflation_t$	-4.456***
	(0.986)
$GDP\ Growth_t$	-0.502
	(1.670)
$Unemployment_t$	-16.530***

	(2.030)
LN Acquiror Net Assets	-0.124***
	(0.033)
LN Acquiror Net Sales	0.241***
	(0.030)
Industry	
Consumer Products and Services	
Consumer Staples	0.316***
	(0.121)
Energy and Power	1.188***
	(0.114)
Financials	0.732***
	(0.096)
Healthcare	0.127
	(0.103)
High Technology	-0.336***
	(0.083)
Industrials	0.185**
	(0.093)
Materials	0.430***
	(0.106)
Media and Entertainment	1.096***
	(0.150)
Real Estate	4.428***
	(0.468)
Retail	-0.030
	(0.128)
Telecommunications	0.331**
	(0.138)
Observations	5137
R^2	0.103
Hausman test of MM against S: chi2(17) = 115.541 Prob > chi2 = 0.000	

Table 8: Robust MM regression results for the relationship between the WX rate and the acquirer debt at takeover at firm level. Standard errors are in parentheses; *p<0.10, **p<0.05, ***p<0.01

First, we look at the Hausman test statistic. The null hypothesis of this test is that there are no outliers present and that MM estimators have the same limit probability as least squares estimators

(Dehon, Gassner, & Verardi, 2012). Because this test statistic has a p-value of less than 0.01 and is thus significant, we reject this null-hypothesis and conclude that there exist outliers in the dataset, and we made the right choice of using robust MM estimators.

We see that the Wu-Xia rate at the time of the acquisition has a negative impact on the relative amount of debt used by the acquirer, significant at 1%. The coefficient has a value of -9.850 which means that the relative amount of debt used by the acquirer decreases with 0.985 for every percentage point increase in the WX rate and vice versa. This finding is in line with the interest rate effect but contradicts the findings by Adra et al. (2020) and Chystiakova (2016). When we look at the industry dummy variable, we see that some sectors use more debt than others. These findings are in line with what we would expect based on the median debt use per industry (Sather, 2022). Debt use is especially higher in more capital-intensive sectors such as energy and real estate.

When we look at the macro-economic control variables, we see that inflation also has a negative impact on the amount of debt used at 1% significance level. For every percentage increase in the inflation rate, the amount of relative debt used goes down by 0.05. The unemployment rate also has a significant negative impact on the amount of debt used by the acquirer. For every percent increase in the unemployment rate, the relative amount of debt used drops with 0.17. The impact of GDP growth is non-significant.

When we look at the firm control variables, we see that the natural logarithm of the acquiring company's Net Assets has a significant negative impact on the amount of debt used whereas the natural logarithm of a company's Net Sales has a significant positive impact on the amount of debt used in the year of an acquisition.

5.2 Findings Multiples

In Table 9 we can see the results of the robust regression with the EV multiple as a dependent variable and the WX rate at takeover and the acquirer industry as explanatory variables

	$EV/EBITDA_{i,t}$
WX_t	10.127
	(7.678)
$Inflation_t$	-15.360**
	(6.718)
GDP $Growth_t$	36.186***
	(10.872)
$Unemployment_t$	-22.644*
	(13.119)
LN Acquiror Net Assets	0.603***
	(0.166)

LN Acquiror Net Sales	-0.337**
	(0.163)
Industry	
Consumer Products and Services	
Consumer Staples	-0.822
	(0.711)
Energy and Power	-2.908***
	(0.604)
Financials	10.489***
	(1.020)
Healthcare	2.674***
	(0.699)
High Technology	2.239***
	(0.640)
Industrials	-1.494**
	(0.592)
Materials	-2.339***
	(0.635)
Media and Entertainment	-0.631
	(0.717)
Real Estate	4.392***
	(1.035)
Retail	-1.182
	(0.725)
Telecommunications	-1.221
	(0.766)
Observations	5314
R^2	0.074
Hausman test of MM against S: chi2(12) = 119.979 Prob > chi2 = 0.000	

Table 9: Robust MM regression results for the relationship between the WX rate at takeover and the target EV multiple at firm level. Standard errors are in parentheses; *p<0.10, **p<0.05, ***p<0.01

The Hausman test statistic is once again significant, indicating that there are in fact outliers present in the dataset and that we made the correct choice of using robust MM estimators. We can see that the Wu-Xia rate at the time of the acquisition has a non-significant impact on the EV multiple paid for the target by the acquirer. This finding contradicts the one by Horn & Fischer (2021) who found that monetary contraction actually worsens firm valuations. The findings also contradict the ones by Bromley & Zhou (2011), who found that lower interest rates are related to lower valuations. However, this result is in line with the finding by Ubl & Brett (2014), who did not find a relationship between EBITDA multiples and monetary policy.

When we look at the macro-economic control variables, we see that inflation and unemployment are both associated with lower multiples, whereas GDP growth is associated with higher multiples.

When we look at the firm control variables, we see that the natural logarithm of the acquiring company's Net Assets are associated with higher multiples whereas the natural logarithm of a company's Net Sales are associated with lower multiples.

5.3 Findings Performance

In Table 10 we can see the results of the OLS regression with the winsorized abnormal acquirer return over the 180-day period after the acquisition as dependent variable, and the average Wu-Xia shadow rate during that period as main explanatory variable. Furthermore, we see the differences between each industry.

	Abnormal Return$_{i,t-1;t+180}$
Average WX$_{t-1;t+180}$	-0.373 (0.344)
Inflation$_t$	0.104 (0.197)
GDP Growth$_t$	-0.418 (0.402)
Unemployment$_t$	0.528 (0.372)
LN Acquiror Net Assets	-0.025** (0.007)
LN Acquiror Net Sales	0.024** (0.007)
Industry	
Consumer Staples	-0.046 (0.033)
Energy and Power	-0.002 (0.029)
Financials	0.044 (0.028)
Healthcare	0.010

	(0.031)
High Technology	-0.006 (0.028)
Industrials	0.005 (0.030)
Materials	0.002 (0.032)
Media and Entertainment	-0.010 (0.035)
Real Estate	0.035 (0.036)
Retail	0.010 (0.042)
Telecommunications	0.000 (0.040)
Observations	1517
R^2	0.024

Table 10: Linear regression results for the relationship between the WX rate and the acquirer return. Standard errors are in parentheses; *p<0.10, **p<0.05, ***p<0.01

We can see that the average WX rate has a non-significant impact on acquirer's abnormal return. We also see that there do not exist significant differences between sectors. I will discuss possible reasons for this in the discussion.

When we look at the macro-economic control variables, we see that none have a significant impact on acquirer returns. As for the firm control variables, the natural logarithm of the acquirer's Net Assets has a negative impact on acquirer returns whereas the natural logarithm of the acquirer's Net Sales has a positive impact on acquirer returns.

6. Discussion

In this section I present a discussion of the findings. I will go over the interpretation of the results, suggestions for possible future research and some shortcomings I have encountered.

6.1 Interest rates' negative impact on debt

Based on the results of regression 1 displayed in Table 8, we cannot reject the first hypothesis stating that interest rates have a negative relation with the relative amount of debt used by acquirers in U.S. M&A transactions. In other words, we identify a relationship between contractionary monetary policy and the amount of debt used by acquirers in M&A. This finding is supported by the results of the robustness check including the negative EBTIDA observations, which are shown in Table 10 in the Appendix. This finding contrasts the finding in the paper by Adra et al. (2020) who found that a rise in the FFR is associated with an increase in the acquirer's indebtedness. However, this finding ís in line with Acharya et al (2022) which corresponds with the interest rate effect as described by Baldwin (2022) in the context of the general economy. His explanation revolved around the fact that as interest rates increase, borrowing will become more expensive and will induce people to borrow less. In essence, this is a simple supply and demand explanation where demand decreases as prices increase. Although it seems logical that this interest rate effect would also be present in the M&A market, just like in other areas of the economy, there was limited empirical evidence for this effect in previous literature. Not only within the M&A market but also in corporate leverage, where Chystiakova (2016) also found a *positive* relation between debt and interest rates. This paper is the first of its kind to find a *negative* relationship between interest rates and acquirer debt in M&A.

However, it is important to note that this paper finds a *relationship* between interest rates and debt, not a causality between both factors. Establishing causality is very difficult, especially within an empirical setting. Causality can only really be established when all other variables are held constant (Kahn & Whited, 2018). Although there is no empirical evidence that there are factors impacting acquirer debt in M&A other than interest rates, it is near impossible to rule out any other possible factors impacting debt, without the risk of overfitting the model. Next to that, because I use a relative measure of debt, it is difficult to rule out whether the debt ratio changes because debt goes up, or EBITDA goes down. EBITDA should not be impacted by a change in interest rates because it does not take interest expenses into account. However, we do have to proceed with caution when interpreting these results because interest rates might still have a certain impact on top line items such as revenue, or all the expenses that the EBITDA does take into account such as Selling, General & Administrative Expenses (SG&A). Nonetheless, I still regard the use of Debt/EBITDA as the most adequate proxy for acquirer debt that was at my disposal. Especially considering the drawbacks of using alternatives such as Debt/Equity that I discussed in section 2.1.4.

6.2 Interest rates' non-significant relationship with target multiples

Based on the results of regression 2 displayed in Table 9, we reject the second hypothesis stating that interest rates have a negative relation with EV/EBITDA multiple valuations that are paid by acquires in U.S. M&A transactions. In other terms, we do not find a significant relationship between the WX rate and the target multiples that are paid by acquirers in a takeover. This finding contradicts the one by Horn & Fischer (2021) and Bromley & Zhou (2011). However, this finding ís in line with the one by Ubl & Brett (2014). Previous empirical evidence on this topic was very inconclusive, with the most important papers finding both a positive, negative and a lack of a relationship between interest rates and valuations. Furthermore, most of the research on the impact of asset valuations was done in the context of stock markets, and not in the context of M&A, which made it difficult to shape an expectation of this relationship in advance. I chose to base my hypothesis on the prediction by monetary policy theory that expansionary monetary policy decreases the cost of borrowing which should increase investment and raise asset price levels and thus increase equity. However, a company's enterprise value is made up of more line items than just equity. As I discussed in section 2.2.1, a listed company's enterprise value is equal to its market capitalization plus the market value of its debt, minus cash and cash equivalents. Because of the research conducted on the relationship between interest rates and debt, we know that acquirers take on more debt as interest rates go down. This should increase a company's enterprise value. We also know from previous research that as investment increases, asset prices increase (Ubl & Brett, 2014). Because interest rates should not impact EBITDA, the only variable item in this calculation is the cash and cash equivalents. In order for this lack of relationship to make sense, there has to be a negative relationship between interest rates and cash (equivalents) that offsets the negative relationship between interest rates and debt. This would not seem logical considering that as interest rates increase, investors should become more incentivized to hold interest-bearing securities such as liquid short-term bonds that fall under cash equivalents. In order to draw a definitive conclusion on this topic, more research is needed on the impact of interest rates on a corporation's cash & cash equivalents.

Moreover, as stated in the discussion on the impact of interest rates on relative debt, it is important to note that although interest rates should not impact EBITDA, we cannot rule out the impact of interest rate on top line items such as revenue, or expenses such SG&A, thereby indirectly impacting EBITDA. Further research is needed to study these relationships in order to isolate the relationship between interest rates and valuations.

6.3 Interest rates' non-significant relationship with acquirer performance

Based on the results of regression 3 displayed in Table 10, we cannot reject the null hypothesis stating that monetary contraction is associated with lower acquirer performance in U.S. M&A transactions. These findings contradict those by Adra et al. (2020), who found that higher interest rates decrease the acquirer performance. Adra et al. studied the acquirer performance on a more short-term study window of the 5 days surrounding the acquisition. As I discussed in section 2.3.1, event studies using short-term performance measures such as the one by Adra et al. should be seen as a study on ex-ante market expectations of the takeover, rather than realized measures of performance (Zollo & Meier, 2008). The finding presented in this paper shows that interest rates do not have a negative impact on acquirer performance in the longer term.

According to the existing literature, there were two possible channels through which monetary policy could influence M&A performance. One was based on an idea presented by Gaughan (2009), where he notes that shareholders benefit from buyers being more cautious about making deals. This combined with the finding by Adra et al. that higher interest rates increase the probability of deal withdrawal led me to conclude that acquirers will be more cautious when interest rates are high, which will improve performance. The other channel was based on an increase in financing costs and stated that because of the increase in financing costs due to higher interest rates, acquirers perform worse. The results presented in this paper seem to suggest that both effects cancel each other out and thereby cause the impact to become non-existent.

Once again, establishing causality is difficult, especially when answering this sub-question. This is because I use stock returns as a proxy for performance. There are many factors influencing a stock's price and in practice, no one is actually able to predict a stock's performance. Taking this into account, I tried to rid the analysis of possible endogeneity problems by looking at possible factors that influence returns discussed in previous literature. Still, it remains difficult to rid the analysis of all endogeneity bias considering that there are many factors influencing stock returns.

6.4 Shortcomings & recommendations for future research

When researching the impact of interest rates on M&A performance, I wanted to correct benchmark returns for possible impact the acquirer might have had on the benchmark's performance in order to limit the bias that might cause. In order to do so, I had to find data on the constituents of each benchmark at the time of the takeover. Data on this was not publicly available whatsoever, and when using the database by Refinitiv Eikon, the constituent data only went back until 2007. The same was true for using the S&P 500 as a benchmark, because Standard and Poor removed this data from the Capital IQ database back in 2020.

This forced me to omit the observations before 2007 which removed a fair chunk of the total number of takeover observations, thus limiting my sample size. Although the sample size that remained was still fairly large, it was a shame I had to omit those observations. If the data were made publicly available, a suggestion for future research would be to investigate the relationship between interest rates and acquirer performance relative to an industry specific benchmark over a longer time period.

Furthermore, the Eikon dataset did not provide a universal company identifier. This made it difficult to supplement the dataset by Refinitiv with possible other datasets. A universal company identifier would have allowed me to also find acquirer stock returns for larger time frames such as 36 months, which was the performance metric that was suggested by Zollo & Meier (2008). Performing similar analysis on different time frames would have allowed me to do robustness checks in order to be more certain of the results.

7. Conclusion

In conclusion, this paper found evidence of a negative relationship between interest rates and acquirer debt in U.S. M&A transactions, which is in line with the findings by Acharya et al. (2022) and corresponds with the interest rate effect as theorized by Baldwin (2022). This finding is important for both academics and practitioners, as it provides an insight that is different from the results found by Adra et al. (2020) and Chystiakova (2016). Furthermore, this paper has identified a non-significant relationship between interest rates and target multiples in U.S. M&A transactions, contradicting the findings of Horn & Fischer (2021) and Bromley & Zhou (2011). This lack of a relationship might be attributed to a possible negative relationship between interest rate and cash equivalents which would offset the negative impact of interest rates on debt. More research is necessary to establish the relationship between interest rates and cash equivalents. Moreover, this paper provides empirical evidence that interest rates do not have a significant relationship with acquirer performance in U.S. M&A transactions, contradicting the findings by Adra et al (2020). These results seem to suggest that both the positive impact of buyer cautiousness and the negative impact of increased financing costs seem to cancel each other out.

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Appendix

Appendix A. Descriptive Statistics

Acquirer Macro Industry	Observations	Mean	Median	σ	Min	Max
Consumer Products and Services	293	21.054	11.494	25.047	4.022	100.978
Consumer Staples	215	15.525	10.770	16.430	4.022	100.978
Energy and Power	616	13.129	9.246	14.608	4.022	100.978
Financials	1731	40.655	32.343	29.890	4.022	100.978
Healthcare	537	23.494	15.033	24.864	4.022	100.978
High Technology	968	28.591	16.653	29.883	4.022	100.978
Industrials	588	14.605	10.341	16.151	4.022	100.978
Materials	323	14.725	9.576	18.276	4.022	100.978
Media and Entertainment	306	19.467	11.956	21.761	4.022	100.978
Real Estate	210	24.280	18.944	20.800	4.022	100.978
Retail	184	17.530	10.978	17.530	4.022	100.978
Telecommunications	233	21.867	11.395	25.832	4.022	100.978

Table 3: Descriptive Statistics Enterprise Value Multiple Data

Acquirer Macro Industry	Observations	Mean	Median	σ	Min	Max
Consumer Products and Services	79	-0.0198	-0.0548	0.2131	-0.3984	0.4128
Consumer Staples	57	-0.0580	-0.0255	0.1742	-0.3984	0.4128
Energy and Power	187	-0.0427	-0.0548	0.2145	-0.3984	0.4128
Financials	391	-0.0194	-0.0255	0.1656	-0.3984	0.4128
Healthcare	149	-0.0350	-0.0264	0.2209	-0.3984	0.4128
High Technology	279	-0.0305	-0.0419	0.2180	-0.3984	0.4128
Industrials	167	-0.0141	-0.0280	0.2140	-0.3984	0.4128
Materials	94	-0.0520	-0.0330	0.2085	-0.3984	0.4128
Media and Entertainment	71	-0.0417	-0.0144	0.2089	-0.3984	0.4128

Real Estate	60	-0.0394	-0.0547	0.1681	-0.3984	0.4128
Retail	37	-0.0174	0.0111	0.2063	-0.3984	0.4128
Telecommunications	49	-0.0096	-0.0002	0.2215	-0.3984	0.4128

Table 5: Descriptive Statistics Winsorized Acquirer Performance Data

Variable	Observations	Mean	Median	σ	Min	Max
WX_t	6204	0.0332	0.046	0.0256	-0.0298	0.081
$WX_{t-1,\ t+180}$	6204	0.0329	0.044	0.0254	-0.0288	0.078

Table 6: Descriptive Statistics Wu-Xia Shadow Rate

Variable	Observations	Mean	Median	σ	Min	Max
$Inflation_t$	6204	0.431	0.041	0.0207	-0.043	0.197
$Inflation_{t-1,\ t+180}$	6203	0.044	0.041	0.0209	-0.028	0.204
GDP $Growth_t$	6204	0.020	0.021	0.015	0.043	0.055
$Unemployment_t$	6204	0.557	0.053	0.014	0.035	0.132

Table 7: Descriptive Statistics macro-economic control variables

Appendix B. Robustness Check

	Debt/EBITDA
$wx\_takeover_t$	-9.034*** (1.037)
$inflation\_takeover_t$	-4.316*** (0.958)
$GDPGrowth_t$	-0.801 (1.649)
$UnemploymentRate_t$	-15.506*** (1.988)
LN Acquiror Net Assets	-0.142*** (0.030)

LN Acquiror Net Sales	0.270***
	(0.026)
Industry	
Consumer Products and Services	
Consumer Staples	0.336***
	(0.119)
Energy and Power	1.196***
	(0.111)
Financials	0.748***
	(0.091)
Healthcare	0.125
	(0.097)
High Technology	-0.294***
	(0.079)
Industrials	0.201**
	(0.090)
Materials	0.453***
	(0.103)
Media and Entertainment	1.067***
	(0.147)
Real Estate	6.531***
	(0.624)
Retail	-0.035
	(0.120)
Telecommunications	0.279**
	(0.129)
Observations	5297
R^2	0.1132
Hausman test of MM against S: chi2(17) = 149.299 Prob > chi2 = 0.000	

Table 10: Robust MM regression results for the relationship between the WX rate and the acquirer debt at takeover at firm level including negative EBITDA observations. Standard errors are in parentheses; *p<0.10, **p<0.05, ***p<0.01

.

Appendix B. STATA Code

```
* I have divided the code for my analysis based on the 3 sub-questions I am
  researching in order to keep the data transformations confined to
  specific questions


* SUB-QUESTION 1: DEBT
        clear

        * Import our dataset
                import excel "/Users/casperfeitz/Master Thesis/Dataset
  Values 10-04-23.xlsx", sheet("Sheet1") firstrow

        * Rename some variables to make them more concise and
  understandable
                rename AcquirorEBITDALast12Months ebitda
                rename AcquirorClosingPrice1DayPri price_tminus1
                rename AcquirorStockPrice180DaysAf price_tplus180
                rename CorrectedWeights weightBM
                rename AvgWXShadowrateDuringHolding avg_wx_rate
                rename WXatTakeover wx_takeover
                rename DateAnnounced date
                rename YearAnnounced year
                rename AcquirorConvertibleDebtLast1 convDebt
                rename AcquirorStraightDebtLast12M strDebt
                rename RatioofEnterpriseValuetoEBI ev_ebitda
                rename DEBTEBITDA debt_ebitda
                rename AcquirorMacroIndustry industry
                rename AcquirerReturn acqret
                rename AdjBenchmarkReturn bmret
                rename AvgInflationduringholding inflation_holding
                rename InflationatTakeover inflation_takeover



        * Drop some values that we used for intermediary calculations and
  no longer need
                drop WeightinBenchmarkDuringTakeo RankDate SDCDealNo
  TargetFullName TargetMacroIndustry TargetMidIndustry TargetNation
  AcquirorMidIndustry AcquirorNation
  TargetFinancialAdvisorsName AcquirorFinancialAdvisorsName
  RankValueincNetDebtofTarg DealStatus MAType NumberofAcquirorStockExchang
  BenchmarkReturn


        * Our categorical variables need to be encoded as such
                encode industry, gen(Industrycodes)
                drop industry
                rename Industrycodes industry

        * We omit all observations with a negative EBITDA due to the non-
  monotonic relationship of Debt/EBITDA
                drop if debt_ebitda <0

        * Drop all observations

        * Generate scatterplot of the WX rate to check for trends
                scatter wx_takeover year
                * Although it is clear that there exists a trend in the WX
  rate over the year, I don't include a trend because this trend should
```

```
already be encapsulated by the inclusion of the WX rate in the regression

	* Generate scatterplot of acquirer debt and the WX rate to check for outliers
		scatter debt_ebitda wx_takeover
		* Find possible outliers

	* In order to deal with outliers, we winsorize the data at the 95th percentile
		winsor debt_ebitda, p(.05) gen(debt_ebitda_winsor)

	* Generate descriptive statistics for the multiple dataset
		sort industry
		by industry: sum debt_ebitda_winsor, detail

	* Use robust MM regressors with an efficiency of 95%
		robreg mm debt_ebitda wx_takeover inflation_takeover GDPGrowth UnemploymentRate LNAcquirorNA LNAcquirorNS i.industry, efficiency (95)

			* Hausman statistic significant which provides us with evidence that MM provide the best estimators


* Now we will run the regression once again without omitting the negative EBITDA observations as a robustness check

	clear

	* Import our dataset
		import excel "/Users/casperfeitz/Master Thesis/Dataset Values 10-04-23.xlsx", sheet("Sheet1") firstrow

	* Rename some variables to make them more concise and understandable
		rename AcquirorEBITDALast12Months ebitda
		rename AcquirorClosingPrice1DayPri price_tminus1
		rename AcquirorStockPrice180DaysAf price_tplus180
		rename CorrectedWeights weightBM
		rename AvgWXShadowrateDuringHolding avg_wx_rate
		rename WXatTakeover wx_takeover
		rename DateAnnounced date
		rename YearAnnounced year
		rename AcquirorConvertibleDebtLast1 convDebt
		rename AcquirorStraightDebtLast12M strDebt
		rename RatioofEnterpriseValuetoEBI ev_ebitda
		rename DEBTEBITDA debt_ebitda
		rename AcquirorMacroIndustry industry
		rename AcquirerReturn acqret
		rename AdjBenchmarkReturn bmret
		rename AvgInflationduringholding inflation_holding
		rename InflationatTakeover inflation_takeover



	* Drop some values that we used for intermediary calculations and no longer need
		drop WeightinBenchmarkDuringTakeo RankDate SDCDealNo TargetFullName TargetMacroIndustry TargetMidIndustry TargetNation AcquirorMidIndustry AcquirorNation
TargetFinancialAdvisorsName AcquirorFinancialAdvisorsName
```

```
  RankValueincNetDebtofTarg DealStatus MAType NumberofAcquirorStockExchang
  BenchmarkReturn


        * Our categorical variables need to be encoded as such
                encode industry, gen(Industrycodes)
                drop industry
                rename Industrycodes industry


        * In order to deal with outliers, we winsorize the data at the 95th
  percentile
                winsor debt_ebitda, p(.05) gen(debt_ebitda_winsor)

robreg mm debt_ebitda_winsor wx_takeover inflation_takeover GDPGrowth
  UnemploymentRate LNAcquirorNA LNAcquirorNS i.industry, efficiency (95)


---------------------------------------------------------------------------

* SUB-QUESTION 2: MULTIPLES
        clear

        * Import our dataset
                import excel "/Users/casperfeitz/Master Thesis/Dataset
  Values 10-04-23.xlsx", sheet("Sheet1") firstrow


        * Rename some variables to make them more concise and
  understandable
                rename AcquirorEBITDALast12Months ebitda
                rename AcquirorClosingPrice1DayPri price_tminus1
                rename AcquirorStockPrice180DaysAf price_tplus180
                rename CorrectedWeights weightBM
                rename AvgWXShadowrateDuringHolding avg_wx_rate
                rename WXatTakeover wx_takeover
                rename DateAnnounced date
                rename YearAnnounced year
                rename AcquirorConvertibleDebtLast1 convDebt
                rename AcquirorStraightDebtLast12M strDebt
                rename RatioofEnterpriseValuetoEBI ev_ebitda
                rename DEBTEBITDA debt_ebitda
                rename AcquirorMacroIndustry industry
                rename AcquirerReturn acqret
                rename AdjBenchmarkReturn bmret
                rename AvgInflationduringholding inflation_holding
                rename InflationatTakeover inflation_takeover

        * Drop some values that we used for intermediary calculations and
  no longer need
                drop WeightinBenchmarkDuringTakeo RankDate SDCDealNo
  TargetFullName TargetMacroIndustry TargetMidIndustry TargetNation
  AcquirorMidIndustry AcquirorNation
  TargetFinancialAdvisorsName AcquirorFinancialAdvisorsName
  RankValueincNetDebtofTarg DealStatus MAType NumberofAcquirorStockExchang
  BenchmarkReturn


        * Our categorical variables need to be encoded as such
                encode industry, gen(Industrycodes)
                drop industry
```

```
		rename Industrycodes industry

	* We omit all observations with a negative EBITDA due to the non-
monotonic relationship of EV/EBITDA
		drop if ev_ebitda <0

	* Generate scatterplot of acquirer debt and the WX rate to check
for outliers
		scatter ev_ebitda year
		* Find possible outliers

	* In order to deal with outliers, we winsorize the data at the 95th
percentile
		winsor ev_ebitda, p(.05) gen(ev_ebitda_winsor)

		* Even more evidence for the existence of possible outliers

	* Use robust MM regressors with an efficiency of 95%
		robreg mm ev_ebitda_winsor wx_takeover inflation_takeover
GDPGrowth UnemploymentRate LNAcquirorNA LNAcquirorNS i.industry,
efficiency (95)
* SUB-QUESTION 2: MULTIPLES

	clear

	* Import our dataset
		import excel "/Users/casperfeitz/Master Thesis/Dataset
Values 10-04-23.xlsx", sheet("Sheet1") firstrow


	* Rename some variables to make them more concise and
understandable
		rename AcquirorEBITDALast12Months ebitda
		rename AcquirorClosingPrice1DayPri price_tminus1
		rename AcquirorStockPrice180DaysAf price_tplus180
		rename CorrectedWeights weightBM
		rename AvgWXShadowrateDuringHolding avg_wx_rate
		rename WXatTakeover wx_takeover
		rename DateAnnounced date
		rename YearAnnounced year
		rename AcquirorConvertibleDebtLast1 convDebt
		rename AcquirorStraightDebtLast12M strDebt
		rename RatioofEnterpriseValuetoEBI ev_ebitda
		rename DEBTEBITDA debt_ebitda
		rename AcquirorMacroIndustry industry
		rename AcquirerReturn acqret
		rename AdjBenchmarkReturn bmret
		rename AvgInflationduringholding inflation_holding
		rename InflationatTakeover inflation_takeover

	* Drop some values that we used for intermediary calculations and
no longer need
		drop WeightinBenchmarkDuringTakeo RankDate SDCDealNo
TargetFullName TargetMacroIndustry TargetMidIndustry TargetNation
AcquirorMidIndustry AcquirorNation
TargetFinancialAdvisorsName AcquirorFinancialAdvisorsName
RankValueincNetDebtofTarg DealStatus MAType NumberofAcquirorStockExchang
BenchmarkReturn


	* Our categorical variables need to be encoded as such
```

```
		encode industry, gen(Industrycodes)
		drop industry
		rename Industrycodes industry

	* We omit all observations with a negative EBITDA due to the non-
monotonic relationship of EV/EBITDA
		drop if ev_ebitda <0

	* Generate scatterplot of acquirer debt and the WX rate to check
for outliers
		scatter ev_ebitda year
		* Find possible outliers

	* In order to deal with outliers, we winsorize the data at the 95th
percentile
		winsor ev_ebitda, p(.05) gen(ev_ebitda_winsor)

		* Even more evidence for the existence of possible outliers

	* Use robust MM regressors with an efficiency of 95%
		robreg mm ev_ebitda_winsor wx_takeover inflation_takeover
GDPGrowth UnemploymentRate LNAcquirorNA LNAcquirorNS i.industry,
efficiency (95)

		* Hausman statistic significant which provides us with
evidence that MM provide the best estimators


---------------------------------------------------------------------------
* SUB-QUESTION 3: PERFORMANCE
	clear

	* Import our dataset
		import excel "/Users/casperfeitz/Master Thesis/Dataset
Values 10-04-23.xlsx", sheet("Sheet1") firstrow


	* Rename some variables to make them more concise and
understandable
		rename AcquirorEBITDALast12Months ebitda
		rename AcquirorClosingPrice1DayPri price_tminus1
		rename AcquirorStockPrice180DaysAf price_tplus180
		rename CorrectedWeights weightBM
		rename AvgWXShadowrateDuringHolding wx_holding
		rename WXatTakeover wx_takeover
		rename DateAnnounced date
		rename YearAnnounced year
		rename AcquirorConvertibleDebtLast1 convDebt
		rename AcquirorStraightDebtLast12M strDebt
		rename RatioofEnterpriseValuetoEBI ev_ebitda
		rename DEBTEBITDA debt_ebitda
		rename AcquirorMacroIndustry industry
		rename AcquirerReturn acqret
		rename AdjBenchmarkReturn bmret
		rename AvgInflationduringholding inflation_holding
		rename InflationatTakeover inflation_takeover


	* Drop some values that we used for intermediary calculations and
no longer need
		drop WeightinBenchmarkDuringTakeo RankDate SDCDealNo
```

```
TargetFullName TargetMacroIndustry TargetMidIndustry TargetNation
AcquirorMidIndustry AcquirorNation
TargetFinancialAdvisorsName AcquirorFinancialAdvisorsName
RankValueincNetDebtofTarg DealStatus MAType NumberofAcquirorStockExchang
BenchmarkReturn


	* Our categorical variables need to be encoded as such
		encode industry, gen(Industrycodes)
		drop industry
		rename Industrycodes industry

	* We ommit all observations before 2007 because we only have
constituent data for the years after 2007, therefore not allowing us to
adjust returns in the years before
		drop if year<2007

	* Generate a value for abnormal return equal to the return in
excess of an industry specific benchmark
		gen abnret = acqret - bmret

	*	* Run linear regression with the wx rate at takeover as
main explanatory variable and the acquirer industry as extra explanatory
dummy variable
		reg abnret wx_holding i.industry

	* Generate descriptive statistics for the acquirer performance
		sort industry
		by industry: sum abnret, detail

	* Generate scatterplot of acquirer performance over the years to
check for outliers
		scatter abnret year
		* Find possible outliers

	* Generate a linear regression post-estimation plot
		lvr2plot, mlabel (abnret)
		* Even more evidence for the existence of possible outliers

	* Use robust MM regressors with an efficiency of 95%
		robreg mm abnret wx_holding inflation_holding GDPGrowth
UnemploymentRate LNAcquirorNA LNAcquirorNS i.industry, efficiency (95)

		* Hausman statistic not significant which provides us with
evidence that MM does not provide the best estimates. Run regression
again using S regressors

		robreg s abnret wx_holding inflation_holding GDPGrowth
UnemploymentRate LNAcquirorNA LNAcquirorNS i.industry

		* Hausman test statistic still not significant so S
estimators do not provide better estimates than regular OLS

	* In order to deal with outliers, we winsorize the data at the 95th
percentile
		winsor abnret, p(.05) gen(abnretwinsor)

	* Generate descriptive statistics for the winsorized acquirer
performance dataset
		sort industry
		by industry: sum abnretwinsor, detail
```

```
	* Regress again using regular OLS and winsorized returns
		reg abnretwinsor wx_holding inflation_holding GDPGrowth UnemploymentRate LNAcquirorNA LNAcquirorNS i.industry

	* Test for heteroskedasticity
		estat hettest

	* Test statistic has a p-value below 0.05. Therefore we  reject the null hypothesis of homogeneity and establish that there doesn't exists constant variance of errors in this set, so we run the regression again with robust errors
		reg abnretwinsor wx_holding inflation_holding GDPGrowth UnemploymentRate LNAcquirorNA LNAcquirorNS i.industry, robust

	* Check to see whether the CLRM assumptions hold
		* Check if average value of residuals is zero
			predict abnret_res, residuals
			sum abnret_res
			* Mean of errors is very close to zero at -1.51e-10 so assumption holds

		* Test for normality of errors using Shapiro-Wilk test
			swilk (abnret_res)

	* Error term is not normally distributed. However, considering the large sample size, the §olation of the normality assumption is virtually inconsequential.    Therefore I disregard this finding for the rest of the analysis and conclude that the CLRM assumptions hold.
```