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How great is the overpricing due to memes?

Does CAPM need an additional meme-factor?

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Abstract (ENG)

After the Co-Vid-19 pandemic and the resulting lockdowns social media platforms played an increased role in the behaviour of the retail traders. The fear of missing out (FOMO) a good investment opportunity becomes an important decision factor at least for the meme stocks that earned a significant social media highlight. In case of the meme stocks the basic capital asset pricing model fails to explain the market prices. Therefore the development of a new model identifying so far unrevealed risk factors is key for the valuation of meme stocks. In order to learn whether an extended version of the CAPM indeed reveals meme factors and thereby reduces overpricing, it is necessary to test the extended model on meme stocks, e.g. on GameStop – the father of meme stocks.

Keywords: meme stock, stock valuation, GameStop, CAPM extension, social media, retail traders' behaviour

Abstrakt (GER)

Nach der Co-Vid-19-Pandemie und den daraus resultierenden Lockdowns haben die Social-Media-Plattformen eine verstärkte Rolle im Verhalten der Privatanleger gespielt. Die Angst vor dem Verpassen einer guten Investitionsmöglichkeit (aus dem Englischen als FOMO abgekürzt) wird zu einem wichtigen Entscheidungsfaktor, zumindest im Falle der Meme-Aktien, welche ein bedeutendes Social-Media-Highlight verdient haben. Bei der Meme-Aktien kann das grundlegende Kapitalvermögens-Preismodell die Marktpreise nicht erklären. Daher gilt, dass die Entwicklung eines neuen Modells, das bisher unentdeckte Risikofaktoren identifiziert, von zentraler Bedeutung im Falle der Bewertung von Meme-Aktien ist. Um herauszufinden, ob eine Erweiterung des CAPM tatsächlich Meme-Faktoren aufdeckt und dadurch die Überbewertung reduziert, ist es notwendig, das erweiterte Modell an Meme-Aktien zu testen, z.B. an GameStop - dem Vater der Meme-Aktien.

Schlüsselworte: Meme-Aktie, Aktienbewertung, GameStop, CAPM-Erweiterung, soziale Medien, Verhalten Privatanleger

Contents

Introduction

The CoVid-19 pandemic started in 2019/20 and triggered economic worries of a crisis. The nature of the crisis was a very different one as that of the previous crises. Besides the ‘new nature’ of the crisis, it can be considered as a contra example of the financial crises in 2008 due to many factors. Policy makers learnt in 2008 that liquidity and quick reactions are key in order to mitigate the effects of a potentially new economic downturn. Therefore central banks and governments imposed restrictions and economic lockdowns in order to prevent the health care system and at the same time a wide range of financial aid was imposed in order to prevent the economy from collapsing.

These two measures – lockdowns and financial support – lead to a controversial situation, in which income flows for businesses and households were provided continuously, despite the fact that households had very limited opportunities for consumption or any other way for spending their incomes.

Financial markets, however, belonged to those few opportunities. To a certain extent they functioned as a substitute for gambling activities and the same time people attributed more attention to trading as well as self-education via social media in order to have necessary knowledge about trading.

As a consequence of the extended use of social media platforms, however, herding behaviour becomes a potential problem. Financial markets continued to perform well despite of the lockdowns. This phenomenon could be interpreted in different ways. Firstly, the increase in the financial markets can be interpreted as the result of the financial support provided by policy makers, i.e. the excess money pumped into the system pushed markets to further rise. Secondly, and more importantly retail traders became determining actors as they allocated much more funds partly based on social media influence to financial markets due to the fact that they had only a couple of other alternatives. Lastly, the increasing markets priced a fast recovery of the economy and reflected optimistic future performance.

The second option describes a herding behaviour and thus it is an explanation by behavioural finance, whereas the first and last options deal with the classical finance point of view. According to the current understanding of financial theory cash flows and risk factors should explain the asset prices, which should be that same as the fundamental valuation.

The currently dominating model for the incorporation of risk is the DCF valuation using CAPM. However, there are several stocks for which the model does not seem to work anymore. These are typically stocks that gain attention on social media platforms like Reddit, Twitter, etc. Therefore it is possible that a 'better than the CAPM' model is necessary in order to value these stocks.

Due to the importance of this issue this thesis aims to find out whether it is possible to perform a better valuation than the basic CAPM in the above mentioned case. It might be the case that new factors are needed additionally in order to explain the price deviations from the fundamental valuations. In other words, the hypothesis is that an extended version of the CAPM should perform better, i.e. the (great extent of) overpricing should vanish with a 'more precise' model.

In order to do so the thesis is divided into five sections as follows. The second section offers an overview of the relevant existing literature and financial theory. First, the impact of social media platforms is elaborated and its relationship to herding behaviour by retail trades is discussed. Second, the two major view of finance – classical view and the behavioural financial view – are shortly reviewed with the extension to modern phenomena in behavioural finance and their relevance to this thesis.

Section 3 deals with alternative models to the basic CAPM. First, the explanatory power of the basic CAPM then alternative models are testes based on the search of potentially missing risk factors, factor for herding behaviour and a combination of these two. The chapter ends with an overview of the limitations of an alternative model.

Section 4 starts with the introduction of the GameStop stock (GME) and then it turns to its valuation using different valuation methods. At the end of this section a football field is used in order to provide an overview of the valuation methods and to be able to deliver a recommendation. Finally section 5 concludes.

2. Literature review

This section begins by highlighting the importance of social media platforms and introduces a selection of existing literature accordingly. Social media has gained a lot of attention from academic research recently. This is also because of the influence of social media on retail traders and their way of collecting information.

The effects of social media, however, are connected to human behaviour and thus it is important to gain an overview about classical and behavioural finance in the second half of this section. Although both classical and behavioural finance are widely known, a general overview is considered to useful in order to have a fully understanding for the modelling part (section 3) of this thesis.

2.1. Social media and herding behaviour

Doubtlessly, financial markets were among the few options, where purchasing remained possible during the lockdown restrictions. Therefore, many professionals argue that the money that was not allowed to be consumed flew (at least partly) into the stock market. As a result stock markets continued to perform well after the sharp break down at the beginning of the pandemic.

It is important to highlight that financial markets could be partly considered as substitute for gambling services and/or that for consumption by retail traders during pandemic. However, retail traders that only invested in the stock market because they lack better alternatives, might have little financial education and understanding about financial markets.

Moreover, these retail traders as well as most of the society were not allowed to leave their homes, but only in very limited cases. As a result of this social media gain significantly on importance and influence – not only in private life, but also in their investing behaviour. Those two facts – social media and the increased attention for financial markets – resulted in a herding behaviour by retail traders.

The increasing popularity and availability of online broker apps, especially on smartphones, enable an access with almost no barriers to financial markets. This provides an easy entry for retail traders, while increasing the gamification of such investments apps thereby potentially contributing to destabilizing herding behaviour (Klein (2022)).

There is a wide range of literature supporting the positive relationship between the influence of social media platform twitter and returns in the stock markets (Yang et al. (2015), Azar and Lo (2016), Sul et al. (2017), Olivera et. al (2017), Reboredo and Ugolina (2018), Duz Tan and Tas (2020)) as well as that in the crypto currency markets (Kraaijeveld and De Smedt (2020)). Similarly, Vasileiou et al. (2021) investigate the effects of Google searches, while Long at al. (2021) study that of the social media platform Reddit.

Their results are consistent with the findings of Tetlock (2007) that highlights the strong relationship between high trading volume and social media influence. He shows that pessimism on social media platforms like twitter can be responsible for downward pressure on market prices even below the fundamental valuation of a stock. He importantly points out that trades encouraged and influenced by social media are consistent with theoretical models of liquidity and noise traders, and thus such trades are not appropriate as a proxy for new information for the established asset valuation models.

Furthermore, there are several studies on documented examples of a herding behaviour and deviation of stock prices from their fundamental valuation in the existing literature. Rubbaniy et. al (2021) could find evidence for herding behaviour in the crypto currency markets. Moreover, they find that herding asymmetry persists during bullish and bearish markets. Their study shows that fear plays a determining role for herding. That is, herding is less prevalent during normal market conditions due to the fact that investors rely on predictions of rational asset pricing models. However, if markets turn down herding phenomenon becomes prevalent (Chang et al. (2000)). Additionally to bullish and bearish regimes, the market extremes play an important role in herding, too. That is, herd investing might be stronger in extreme markets. (Demirer and Kutan (2006)).

The crypto currency market is, however, not the only example for herding behaviours. Vo and Phan (2017) found evidence for herding behaviour in the Vietnamese stock market. However, this herding behaviour is not typical for the Vietnamese stock market only, but generally for stock markets. Shiva et al. (2020) investigate the Indian stock market and focus in particularly on the impact of Nomophobia (No-Mobile-Phobia) and how it relates to investment decisions and herding behaviour. They incorporate the role of investor related fear-of-missing-out (I-FOMO), i.e. the information asymmetry generated by the absence of a mobile device combined with the fear of missing out important information for investing in financial markets. They identify a tendency for overtrading by retail traders in case of fear of no investment information and lack of confidence due to news in smartphones.

The epicentre of the herding phenomenon was, however, the US listed GameStop stock. In January 2021 there was a cult like run on purchasing the shares of the company (Hasso et al. (2022). However, that large increase in price was not a response to an economic event, but the cult like – and partly speculative – trading by retail traders influenced by social media (Chohan (2021)).

Other meme stocks like AMC, Tilray or Nokia experienced similar runs later on, especially after so-called due-diligence posts on Reddit (Bradley et al. (2021)). Although these due-diligence posts by nonprofessional investment analysts trigger a strong herding behaviour (Dim (2021)), the phenomenon – including the short squeeze – turned out to be the most significant in case of GameStop stock.

De Long et al. (1990) documented that stock prices can deviate due to noise trader's sentiment. The reason for that is the limited information availability of retail traders compared to institutional investors. Institutional investors are generally known better informed than retail traders as they have much more opportunities to monitor stocks. (Boehmer and Kelly (2009)). However, information accessibility became much easier for retail traders via social media platforms (Chen et al. (2014)). Consequently, retail traders are strongly affected by sentiments from social media platforms. Social media influence can lead to cognitive and psychological biases and result in less rational investment decisions by retail traders (Black (1986)).

On the other side Jarrow and Li (2021) show that in case retail traders form groups based on information provided on social media platforms, they can discipline the short selling incentives of large trader, like institutions, and thereby uniformly improve social welfare. Of course, the price of a stock depends on both the institutional and the retail traders beliefs (Behrendt and Schmidt (2018)). Therefore a herding behaviour created by sentiments from social media platforms can result in prices that are far above from their fundamental valuations. Hasso et al (2022) find evidence that in the case of GameStop, indeed, a group of retail traders were the ones that created a frenzy and were therefore responsible for the deviation of stock price from its fundamental valuation.

Following this consideration, Umar et at. (2021) study the relationship between the returns of GameStop and the sentiment driven by pricing. They investigate whether the impact of social media creates inefficiency in the market, i.e. whether social media contributes to a significant deviation in case of the stock price of GameStop from its fundamental valuation. Their results show that the returns of GameStop have been possibly positively affected by investors sentiments influenced by social media platforms.

As also the example of GameStop shows it is of high importance to understand whether the role of social media and its affects to valuation models. As Angel (2021) points out the bubble and collapse of GameStop resulted in collateral damage not only for those participating in trading the stock, but also index-funds – and through that potentially the whole market.

Aloosh et al. (2022) generalize the investigation and concentrate on a specific broader group of stocks, the meme stocks – instead of studying only one individual stock, e.g. GameStop.

Generally, a meme is an idea, behaviour, or style that is spread via social media platforms and especially for humorous purposes. This general definition of memes, however, can differ for industries (Börzsei (2013)). In finance, memes reveal in the form of meme stocks. A meme stock is a stock that has seen an increase in volume not because of how well the company performs, but rather because of hype on social media and online forums. Consequently, due to their popularity meme stocks are overvalued.[1]

In order to analyse the market efficiency Aloosh et al. (2022) form two meme indices and test them on the S&P 500 index. Their first index, MS 50, consists of equally weighted portfolio of stocks that were restricted by Robinhood app on 28th January, 2021. The second index is the MS 8 index, i.e. portfolio of stock with the same criteria, but still restricted on 1st February, 2021. After employing robust testing they find that meme stock trading does not degrade market efficiency.

Therefore the question arises whether the pricing models need to be adjusted given the market functions efficiently. Are there any additional risk factors needed despite the market was already found to be efficient? This thesis studies that question and attempts to find an answer by developing and testing new valuation models.

2.2. Financial Theory

In order to derive the 'right' valuation model it is important to have an overview about the recent standpoint of financial theories. There are two major financial theories – the classical point of view and the behavioural financial point of view. The current academic position is that classical finance should be used for fundamental analysis, in order to derive the fair value of an asset. On the other hand behavioural finance is gaining on importance and is a widely researched field of finance.

Classical finance states that the value of an asset is determined due to risk factors. However, it might be the case that not all risk factors are known and therefore mispricing can persist. Consequently, in case all risk factors are known the price of an asset must equal its fundamental value (Fama (1970)).

On the other hand behavioural finance takes the limited capabilities of humans into account. This theory states that asset prices can be different from the intrinsic values

[1] https://www.thebalance.com/what-is-a-meme-stock-5118074 (12th June 2022)

because of these ‘human factor’ and therefore mispricing might persist even for a longer time (Shiller (2003)).

There is still an ongoing debate whether it is the human behaviour or some unknown risk factors that should explain misprices in the financial markets. This thesis tests valuation models mostly via the classical financial theory point of view, while also trying to consider factors that have behavioural financial characteristics.

2.2.1. Overview: Classical finance

Classical finance deals with fundamental analysis of asset prices. As mentioned above, one of the core stones of classical finance is the efficient market hypothesis (EMH) by Fama (1970). Other important elements are the Modern Portfolio Theory (MPT) by Markowitz (1952) and the Capital Asset Pricing Model (CAPM).

According to the EMH prices should only change if there is new information. In other words, the market is said to be information efficient if prices fully reflect available information. In such an efficient market it is not possible to make any profits by trading on a given information set. The definition of this information set determines the forms of the market efficiency.

There are three different types of market efficiency – the weak form, the semi-strong form and the strong form. In case of the weak form of market efficiency, the information set is information about historical prices, i.e. it is not possible to make profit by trading on historical patterns (i.e. trading on technical analysis). In case of the semi-strong form of market efficiency, the information set is publically available information, i.e. it is not possible to make any gains by trading on fundamental analysis. Last, but not least, the strong form of the market efficiency describes the case when the information set is all (incl. private) information, which implies that no economic benefits can be realised by trading on insider information.

Furthermore, the EMH states that investors are rational. Even if there are noise traders, i.e. investors trading irrational, their trade is random and cancels each other. In case, there is a herd of noise traders, arbitrageurs will trade in such a way that prices are driven back to their fundamentals. Anomalies are therefore considered as unknown risk factors. That is, the EMH states that market prices are always correct.

The EHM is a central assumption for the MPT. Markowitz (1952) shows that all efficient portfolios lie on a curved line in a mean-variance space. Following Markowitz' work Tobin (1958) finds that the addition of a risk-free asset to the investment opportunity set, leads to the separation of the individual preferences and the risky portfolio. He argues that all investors should purchase the same portfolio of risky assets and their level of risk-aversion should only affect the balance of that risky portfolio and a risk-free asset (Tobin's Separation theorem). Importantly, Tobin assumes that investors are rational and mean-variance optimizers.

Applying the above theory by Markowitz (1952), Sharpe (1964) states that all investors minimize the variance for a given return, therefore a pricing formula can be derived independently from individual preferences. This pricing formula is known as the CAPM.

2.2.2. Overview: Behavioural finance

In contrast to classical finance, behavioural finance does not accept the EMH and that idea of unknown risk factors as explanation for the anomalies. Shiller (2003) argues that financial markets often do not behave in a way as traditional economic theory would predict. Instead, large and sustained mispricing can be created. This is simply because decisions are made by humans and humans have limited rationality, social preferences and lack of self-control (Kahneman et. al (1991)).

Following the theory of behavioural economics introduced by Shiller and Thaler, Barber and Odean (2013) identify ten behavioural patterns of individual investors. Each of these can lead to sustained mispricing due to the human factor.

1. Overconfidence bias: Uninformed individuals tend to overestimate the precision of their own knowledge. Overconfidence supports excessive/aggressive trading, which usually results in a worse performance.
2. Self-attribution bias: People attribute their success to their own skills, but blame bad luck for unsuccessful ones.

3. Sensation seeking bias: People’s desire for hope and intense risk-taking. That is, trading is like an entertainment and is interesting for those like gambling.
4. Familiarity bias: People overinvest in countries, industries, companies, etc. they know. They do this in order to avoid ambiguity.
5. Disposition effect bias: People tend to hang on badly performing stocks and sell well performing ones, i.e. people are risk-takers on loosing stocks as they do not want to admit that they made a mistaken trade.
6. Anchoring bias: People either overreact or underreact new information or they trade based on irrelevant information expecting the trends to continue (consistent with the findings of Black (1986)).
7. Attention bias: People have limited attention for investing, therefore they are more likely to buy stocks that have recently appeared in the news and attracted their attention.
8. Investors’ mood bias: People trade depend on if they feel good or bad based on other (for the trading actually irrelevant) factors.
9. Experience bias: People tend to believe to their own experience rather than considering historical evidence.
10. Herding bias: People follow the trade of other people.

It is interesting to highlight that meme stock traders were probably affected stronger by some of the biases, like herding, sensation seeking, overconfidence and familiarity bias, whereas other biases might have played a much less important or even no role.

In addition to these biases, there are some new phenomena during the pandemic. Firstly, the fear of missing out (FOMO). FOMO is associated with a fear of regret, i.e. traders may be concerned about missing a potential profitable investment. In other words FOMO is characterized by a desire to stay connected all the time with what trades other actors are doing (Przybylski et al. (2013)).

Secondly, the phenomenon of ‘there is no alternative’ (TINA). TINA is often used by traders in order to explain a less-than-ideal portfolio allocation, typically of stocks, because other asset classes perform even worse. This situation and the subsequent decisions of traders might lead to the "TINA effect" whereby potentially the only reason for the price increase of stocks is the lack of alternatives.[2]

Last, but not least, social media platforms encourage retail traders to buy the dips (BTD). BTD means purchasing an asset after it has dropped in price. The belief here is that the new lower price represents a bargain as the "dip" is only a very short-term blip and the stock is likely to bounce back and increase in value.[3] Therefore, the concept of buying dips is based on the theory of price waves.

Generally, all new phenomena could be seen as a subcategory of herding behaviour, therefore highlighting the importance of this pattern especially during the pandemic.

3. Models

In this section different valuation models are going to be tested. The starting point is the generally used CAPM. The purpose of the newly developed models is a better understanding of the pricing of a special group of stocks – the meme stocks.

According to classical finance a price of a stock must be equal to its fundamental valuation, which in turn is determined by risk factors. This means in a CAPM framework that any security is determined by its market beta and the risk-free rate. Extending the CAPM framework allows new risk factors, too.

New risk factors are of particular interest in this thesis as the CAPM framework seems not to work well enough for the meme stocks. Therefore it is important to know, whether a new framework, i.e. a new pricing model is needed or the CAPM proves to remain the most appropriate model.

[2] https://www.investopedia.com/terms/t/tina-there-no-alternative.asp (10th May 2022)
[3] https://www.investopedia.com/terms/b/buy-the-dips.asp (10th May 2022)

3.1. Hypothesis, data and methodology

The reason for challenging the CAPM in case of the meme stocks becomes clear on the example of the best known meme stock during the pandemic – GameStop (GME). As November 2022 the analyst target price for a GameStop is $ 37 per share, while it trades at a close price close to $ 200 per share (Yahoo Finance). This is a great deviation between stock price and fundamental valuation.

Interestingly, GameStop is not the only meme stock with such a behaviour. Therefore it is important to understand whether an extension of the CAPM can mitigate this great difference. The hypothesis of this thesis is that an extended version of the CAPM can indeed perform better on the valuation of meme stocks, i.e. the (great extent of) overpricing vanishes with a model consisting more (significant) risk factors.

In order to investigate this hypothesis the data of asset prices have been sourced from Yahoo Finance[4] and S&P Capital IQ[5]. Regarding the stock prices, indices and the risk-free rate, daily data have been collected in the period of January 2020 to November 2022 and then used in order to perform the tests and valuations for this thesis. Regarding the time horizon, the period above has been selected as the deviations between price and fundamentals are expected to be the most prevalent following the outbreak of pandemic.

Based on the daily prices for selected stocks and indices, annualized daily returns have been calculated for the further analysis. It is important to consider daily returns as social media has a large and more importantly quick influence on meme stocks. Due to the fact that this influence might changes very fast, and so do the price of the meme stocks, it is reasonable to select a short period of time for the analysis, i.e. daily basis. A longer time frame, i.e. weekly or monthly data, could lead to vanishing effects as different meme movements might offset each other. On the other hand it is not

[4] https://finance.yahoo.com/?guccounter=1&guce_referrer=aHR0cHM6Ly93d3cuZ29vZ2xlLmNvbS8&guce_referrer_sig=AQAAADgh5Xh41zhG4tXGAgc_Vvq1pdh-o6071cIGHK9LuVGaVN2qObWFO1t4Wvc8oGDvf3LO8G7dp67J8Vh5u5208KTdXJE9Ii2PQNQRyKD90MMvpkp0coAoB5sKjHost6GFPJyVnmHT4SfFiFdgyePfDqAgSIM2e0USpD8KxWgW5ngW (12th June 2022)

[5] https://www.spglobal.com/marketintelligence/en/campaigns/sp-capital-iq-pro?utm_source=google&utm_medium=cpc&utm_campaign=CIQPro_Search_Google&utm_term=capital%20iq&utm_content=542966230023&_bt=542966230023&_bk=capital%20iq&_bm=e&_bn=g&_bg=128384020444&gclid=EAIaIQobChMIv6TO-bao-AIVa5BoCR24BAG3EAAYASAAEgI-rvD_BwE (12th June 2022)

necessary to apply returns with a higher frequency because news typically lose space of their momentum after a few days.

Furthermore, due to the rather short investigation period, the risk-free rate is defined as the one-year treasury rate in this thesis. It is important to highlight that the existing literature defines the risk-free rate as the ten-year treasury rate most of the time. However, the respective investigated periods are usually longer. Therefore the choice of the risk-free rate is considered to be justified.

The methodology for processing the given data is to build a meme portfolio and apply an OLS regression on selected factors in order to test the different new models. In case the additional factors turn out to be significant and the model can predict the meme stock price with a greater explanatory power, the model is considered to be a more appropriate one than the basic CAPM.

The meme portfolio for testing consists of three stocks: GameStop, AMC and Tilray. All of them show typical meme stock characteristics as there was a great hype in their trading records as well as they received great attention on social media platforms during the pandemic.

In addition to this meme portfolio the S&P 500 index is used as a proxy for the market portfolio. Moreover the VIX index is used as a proxy for fear, which is tested as a potential factor for newly developed models. The CBOE Volatility Index (VIX) is a real-time index that represents the market's expectations for the relative strength of near-term changes in the price of the S&P 500 index (SPX). Because it is derived from the prices of SPX index options with near-term expiration dates, it generates a 30-day forward estimate of volatility. [6] Volatility, i.e. the speed of which prices change, is often considered as an indication in particular for the degree of fear among traders.

The motivation for introducing fear as a risk factor takes behavioural financial views into account and transfers it into classical financial perspective. In other words fear is considered as a risk factor and is incorporated into the alternative models. In case of

[6] https://www.cboe.com/tradable_products/vix/ (12th June 2022)

meme stocks herding appears to be a major issue. As described in section 2.2.2 herding is either a fear of downturn market movements or it is FOMO.

There are different methods for measuring fear of crisis and FOMO. In this thesis one measurement uses the VIX index, the other one applies dummy variables. Besides both of this methods there are also other factors tested for the new models and therefore examine whether the extension of the basic CAPM is reasonable.

3.2. Development of new models

In this part of the thesis the alternative models are going to be tested using the methodology described above. The aim of the tests is to identify which model is significant and has an explanatory power greater than the basic CAPM.

In order to be able to make comparisons to the basic CAPM, the significance of the CAPM during the investigated period is tested at first. The model is as follows:

$$basic\ CAPM = r_{free} + \beta_{market} * r_{market} \quad (1)$$

Importantly, the result for β_{market} is significant at 0.1 % level. This means that the CAPM holds also during the investigated period. On the other hand the adjusted R^2 is relatively low, i.e. 0.01929. This finding is key as these results show that the CAPM holds, but there is potential for an improvement in explanatory power.

By developing new models the motivation is to increase this explanatory power by involving additional sentiments (risk factors).

The first alternative model considers a purely behaviour financial perspective and tests for herding with a dummy based on the positive or negative return of the previous day. That is the alternative model appears to be:

$$alternative\ CAPM_1 = r_{free} + \delta_{herding0} * herding_0 \quad (2)$$

This model indicates that meme stocks are valued only based on the risk-free rate and the result of the previous day. It is important to highlight that such a model would contradict existing pricing theories due to the lack of ‘non-human factors’ and therefore no significance is expected. This is indeed the case. The model is not particularly meaningful, but might be considered as a starting point for testing the effects of herding.

The zero in the lower index of the variable indicates that the dummy has been set to 1, in case the return of the meme portfolio was greater than zero in the previous day and zero otherwise. As a modification of the above models and that of models below the + / - 5 % threshold is also tested, but not shown in the thesis as the results are the same.

This leads to the second alternative model, which still attempts to incorporate the effects of herding behaviour, but it does so by extending the basic CAPM with a dummy variable. The alternative model is therefore:

$$alternative\ CAPM_2 = r_{free} + \beta_{market} * r_{market} + \delta_{herding0} * herding_0 \quad (3)$$

Although the coefficient for the market is significant on the 1 % level, the herding dummy fails to be significant. Therefore also this alternative model fails to be an extended model of the basic CAPM.

In the following, the VIX index is used for testing for herding instead of dummy variables. The same logic is used, i.e. first the pure VIX index is used as the following model shows:

$$alternative\ CAPM_3 = r_{free} + \beta_{VIX} * r_{VIX} \quad (4)$$

As it could be expected this model reveals no significance and thus this alternative model is not appropriate for meme stock valuation.

The next alternative model is similar to (3) in the sense that the basic CAPM is extended, however, in this case with the VIX index as factor for measuring herding effects. The model is as follows:

$$alternative\ CAPM_4 = r_{free} + \beta_{market} * r_{market} + \beta_{VIX} * r_{VIX} \quad (5)$$

It turns out that this model is, indeed, significant. The sentiment for the market is significant, whereas the sentiment for the VIX is significant only at the 0.1 % level. This means that the significance of the market sentiment improves in comparison to the basic CAPM (model (1)) and at the same time the additional factor is significant, too.

Regarding the explanatory power of (5), there is an improvement to the basic CAPM, too. The adjusted R^2 becomes greater, i.e. 0.03647. This implies that this model, indeed, performs better than the (1). In other words extending the basic CAPM with the VIX factor results in greater significance and greater explanatory power and thus it is considered as a more appropriate model for the valuation of meme stocks.

In order to examine further potential for increase in explanatory power, the extended CAPM is tested for additional factors by taking the squares into consideration, i.e.:

$$alternative\ CAPM_5 =$$

$$= r_{free} + \beta_{market} * r_{market} + \beta_{market}^2 * r_{market} + \beta_{VIX} * r_{VIX} + \beta_{VIX}^2 * r_{VIX} \quad (6)$$

The results show that the market sentiment is significant, whereas the squared market beta and the VIX sentiment are only significant at the 1 % level. The squared sentiment for VIX is failed to be significant.

Due to the lack of significance of the last term, the regression is tested once again, however, without the insignificant term. That is:

$$alternative\ CAPM_6 = r_{free} + \beta_{market} * r_{market} + \beta_{market}^2 * r_{market} + \beta_{VIX} * r_{VIX} \quad (7)$$

The effect of the modification of the model is that the significance for the market remains the same, whereas the significant for the VIX beta increases, it is significant at the 0.1 % level. The squared market sentiment remains significant, although only at the 5 % level. Also the explanatory power of the model increases in comparison to (1) and (5). The adjusted R^2 amounts to 0.04155. The sentiments for market, squared market and VIX appear to be 1.789, -8.559 and 0.267, respectively.

Concluding, there are some alternatives model, which have a greater explanatory power and are significant at the same time. Due to the fact that (7) appears to have a greater explanatory power than that of (1) or (5) and significant for all tested factors – unlike (6) – it is considered to be the most appropriate extension of the CAPM [hereafter extended CAPM] among the investigated alternative models.

3.3. Limitations

Although the extended CAPM is considered to be more appropriate in terms of the above in case of the meme stock valuation, it is to be used with care. It is important to highlight the source of shortcomings for the alternative models and data. Due to these limitations the results of this thesis might be challenged. In addition alternative modelling can lead to different interpretation of data.

First and most importantly, the models are based on only a relatively short period of time Jan 2020 to Nov 2022. Although due to the use of daily data there are 461 data points (returns), the period might not be long enough in order to observe patterns that hold in the long-term, too. However, a longer period is not possible due to the fact that data earlier than Jan 2020 is not effected by the Co-Vid crisis and thus not subject to the analysis of this thesis.

Second, the choice of the meme portfolio, especially its composition, i.e. amount of stocks and the definition of these meme stocks, is key. In case of this thesis the definition of a meme stock is that there must be an “irrational rush” on a stock combined with social media hype in the investigated period.

In order to illustrate how sensitive is the meme portfolio to the definition, there is a contra example. There might be stocks with a run and / or popular on social media platforms, but not in the investigated period. Such an example is Tesla (TSLA). Tesla stock has experienced a run and was often present in the social media, however, this was not a typical phenomenon in the investigated period. That time Tesla behaved as a growth stock rather than a meme stock.

Moreover the number of meme stocks fulfilling the definition is limited. In case of this thesis the meme portfolio consist only three meme stocks. Of course, the more stocks the portfolio consist, the greater is explanatory power of the applied model for meme stock valuation.

Last, but not least the timing and the horizon are determining factors for the alternative models. It was already explained that the investigated period, i.e. the length of the period (horizon) highly influences the composition of the meme portfolio and thus the results of the alternative models. However, it is also important whether a meme stock behaves as such from the beginning of the horizon or only after some time (timing). This is important as a meme stock ideally fulfils the definition during the whole investigation period so it can be part of the meme portfolio. Especially due to the limited size of the meme portfolio, rebalancing in such a short period would lead to distorted results and thus it is to be avoided.

Given these limitations the application of the extended model using the meme portfolio and data above might be challenged.

4. Empirical part

In this section the father of meme stocks, GameStop (GME) is going to be valued with different methods in order to investigate whether overpricing still persist after applying the extended CAPM described in section 3.2.

4.1. About GameStop (GME)

GameStop became the most traded stock on 26th January 2021 through the social media impact especially through Facebook, Twitter and Reddit.[7] These platform created a cult-like phenomenon. As a result of this hype the stock price of GameStop rose at the peak of the hype to its 28-fold, e.g. from $ 17 per share to $ 500 per share. This is doubtless an incredible growth without a major change in the firm's capital structure, policy or any other factor that should imply any major change in the stock price according to classical financial theory.

In order to get a better understanding of the company and to be able to perform the fundamental analysis it is important to have a basic knowledge about what the firm does. GameStop Corporation operates specialty electronic game and PC entertainment software stores and is headquartered in Grapevine, Texas (USA). The

[7] The Wall Street Journal (27th Jan 2021) https://www.wsj.com/livecoverage/amc-gamestop-stock-market/card/FLBEJbdOhyIDnViitKgf

Company stores sell new such as used video game hardware and software, as well as accessories.[8] GameStop Corp. is the largest video game retailer worldwide.[9] As of January 30, 2021, GameStop had a total of 4,816 stores across all of its segments; 3,192 in the United States, 253 in Canada, 417 in Australia and 954 in Europe.[10]

It offers a range of products in various categories, which include hardware and accessories, software and collectibles. As the category hardware and accessories the firm offers new and pre-owned video game platforms from the major PC and console manufacturers. In the software category GameStop offers new and pre-owned video game software for current and some prior generation consoles. It also sells a wide variety of e-commerce properties. Collectibles consist of licensed merchandise, primarily related to the video game, television and movie industries and pop-culture themes which are sold through the physical video game stores as well as e-commerce properties.[11]

Regarding the financial situation of GameStop it is important to highlight that the Co-Vid-19 lockdowns had a significant impact on the firm's business. The mandatory closures of the stores due to governmental restrictions led to a dramatic drop in sales. In addition, revenue has been declining in the previous years due to the growing market share of online shopping, which is a great challenge for GameStop's business model that is based on retail stores. Moreover, the firm's business is seasonal. A major portion of the company's sales and operating profit is realized during the fourth fiscal quarter, which includes the holiday selling season.[12]

[8] Bloomberg (19th June 2022), https://www.bloomberg.com/quote/GME:US
[9] Insider (19th June 2022), https://www.businessinsider.com/gamestop-worlds-biggest-video-game-retailer-decline-explained-2019-7
[10] Annual Report GameStop (2020), p.1.
[11] Annual Report GameStop (2020), p.1-2.
[12] Annual Report GameStop (2020), p.3-4.

4.2. DCF valuation

Given how GameStop is operating and what challenges the firm is facing leads to a better understanding of the drivers of the fundamentals. These drivers will be taken into account for the estimation of the intrinsic value of the stock during the DCF valuation.

The DCF valuation projects the cash flow of the company based on the above mentioned drivers. These cash flows then discounted and the discount rate based on the CAPM – both considerations, basic and extended CAPM.

4.2.1. Forecasting important statement positions

In order to perform a DCF valuation the cash flows have to be estimated. Therefore it is necessary to start with the forecasting of the company's revenue and derive the cash flows from that. The revenues of the last five financial years (2017 – 2021) are the starting point of the estimation. Sales are forecasted for four years (2022 – 2025). There are two tables in the appendix – Table 6 and Table 7 – showing these figures.

It is important to highlight that GameStop operates in a cyclical industry. As such demand is greatest and thus revenue is highest in the early years of a cycle. The last year of a cycle are typically the ones with poor performance. As end of 2020 a new cycle was being started.[13]

Despite of this fact above, 2021 sales declined even more than in the previous year. Sales decline in 2019 – 2021 were -1.3%, -22.5% and -24%, respectively. This result is clearly the result of several factors, most importantly the end of the last cycle, the firm's loss of sales against online shops and the lockdowns due to Co-Vid-19 pandemic. These negative effects are considered to be partly short-term. It is expected that revenue in 2022 will grow fast and be positive due to the fact that retail shops are no longer forced to close down and additionally the high demand at the beginning of

[13] Annual Report GameStop (2020), p. 25.

the new cycle ensures the rise of sales. Furthermore, it is important to highlight that GameStop carried out the closures of about 1,000 stores bw. 2019 – 2020. This cut in expenses was necessary in order to return back to profitable business. Regarding the revenue estimation it is assumed to be a sufficient action in order to stop the significant decline of sales of the last two years and drive back the business to a healthy operation. In addition, the firm is focusing on the US, its greatest geographical market and wants to invest in e-commerce capacities. All these actions should support the return back to a positive revenue growth course.

It is expected that the bounce back is going to be strong after the lockdowns and after store closures. A sales growth of 10.3% is estimated for 2022 – twice as much as 2018. Sales growth for the next two years are estimated to be only about 75% of that of 2022. Finally, 2025 is an estimated start of the next cycle and thus sales expected to grow the same pace as in 2022. However, after these four years with rather large revenue growth the pace of growth is expected to slow down as most of restructuring and anti-lockdown effects are vanishing. Thereafter a period of slow, but long-term growth is expected.

Despite the assumption of the successfully return to profitable business it is important to highlight that GameStop is not expected to return back to its level of sales until the end of the estimation period. Sales 2017 amounted to about $ 7.97 billion, but that estimated for 2025 is only $ 7.13 billion. In other words the firm is expected to drive back to profitability, but the recovery from the depressed years should take several years.

Regarding the composition of the revenue, the largest market, the USA is estimated to have the smallest growth, while the European and Australian markets can be considered as fast growing or recovering markets.

After the revenue estimation the gross profit margin is to be forecasted. It is assumed that the Cost of Goods Sold (COGS) relative to revenue is relatively stable between 72-73%. For the estimation of this rate a four year rolling average is used. Although

COGS are estimated to rise from $ 5.6 billion to $ 7.2 billion in 2022 – 2025, the gross profit margin is forecasted to remain stable at 27-28 %.

The next positions to be estimated on the income statement are the Selling General & Admin Expenses (SGAE). This is an important position as the closures of the stores should make a significant effect on SGAE. The ratio of SGAE to revenue is 30% in 2021 (last financial year). SGAE to sales in 2022 is expected to decline 1% and thereafter 1.5% thus 2025 reaching the level of 2018 (last year with positive sales growth).

Consequently, the operating margin is increasing. The operating margin for the first forecasted year is still negative with –0.8 %, but expects a recovery after last financial year that resulted in –4.9 % operating margin. The EBIT (operating) margin is estimated to reach 2.7 % until the end of 2025 by growing from 0.3 % to 1.7 % in 2023 and 2024 respectively. 'Table 8: Forecasting important items' in the appendix shows the above mentioned figures.

4.2.2. Forecasting FCFE and long-term growth

After the top down forecast of the income statement positions and arriving to the EBIT, the free cash flow to equity (FCFE) is going to be projected. First, the EBIT and the tax rate of the company is used in order to forecast the company's net operating profit after tax (NOPAT), then depreciation and capital expenditures (CapEx) as well as the change in net working capital (NWC) are forecasted. Finally, FCFE is calculated. Table 9 in the appendix show the figures.

GameStop is effectively taxed at 20.49% as of 2021. This tax rate is assumed for the forecasted years. Therefore deriving the NOPAT the EBIT is multiplied by one minus this tax rate. CapEx and depreciation are estimated to sustain the same level relative to revenues. It is important to highlight that the firm reported in its last annual report that no goodwill remained, thus the goodwill (and its depreciation) is zero for the estimation period.

The last term to estimate for the FCFE is the change of the NWC. NWC is the sum of inventory and accounts receivable minus the accounts payable. It is assumed that all position is going to sustain the average of the last four reported years in all estimation years. The change of the NWC (dNWC) is a yearly change. Table

In the next step depreciation is added to NOPAT, while CapEx and dNWC are subtracted from it. Therefore the FCFE is calculated and turns out to be about $ 66 million, $ -16 million, $ 54 million and $ 99 million from 2022 to 2025, respectively. 2026 is the exit year in which the terminal value is estimated based on the long-term growth rate. Figures are listed in Table 10 in the appendix.

	WEIGHT	**GDP GROWTH**
USA	67.14 %	1.70 %
CANADA	5.08 %	1.50 %
AUSTRALIA	12.29 %	2.30 %
EUROPE	15.50 %	1.45 %
LONG-TERM GROWTH		**1.72 %**

Table 1: Long-term growth

The long-term growth rate consists of two components: the weights of geographical markets and their GDP growth rate. The US segment accounts for about two third of the firm's revenue and the GDP growth forecast for the USA is 1.70 %.[14] Second largest segment is Europe making out 16 % of the company's sales and contributing with 1.45 % GDP growth. Australia and Canada account for 12% and 5% of the sales and have a GDP growth rate of 2.30 % and 1.50 %, respectively. Therefore the weighted average of the GDP growth rate among the segments is a good estimation for GameStop's long-term growth. This amounts to 1.72 % as it is shown in Table 1 above.

The long-term growth plus one multiplied by the last forecasted FCFE has to be divided by the WACC minus the long term growth rate in order to derive the terminal value.

[14] https://www.statista.com/statistics/263614/gross-domestic-product-gdp-growth-rate-in-the-united-states/
https://www.statista.com/statistics/263603/gross-domestic-product-gdp-growth-rate-in-canada/
https://www.statista.com/statistics/263602/gross-domestic-product-gdp-growth-rate-in-australia/
https://www.statista.com/statistics/267898/gross-domestic-product-gdp-growth-in-eu-and-euro-area/
all links as 10 December 2021

The value of the WACC (weighted average cost of capital) depends on the definition – either by using the basic or the extended CAPM. This difference will be evaluated later in this thesis. All FCFE and the terminal value have to be discounted by the WACC. The sum of the discounted cash flows lead to the estimation of the enterprise value. That minus net debt, minority interest and pension liabilities result in the firms market capitalization or equity value. As the very last step the market capitalization is divided by the number of shares outstanding and thus the price per share is determined. GameStop has 69.3 million shares outstanding as of 2021, no minority interest, $ 5.6 million in pension liabilities as well as a net debt of $ -1 million.

4.2.3. Estimation of WACC

Turning to the estimation of the weighted average cost of capital the risk-free rate has to be chosen appropriately. Usually, the risk-free rate is defined as the 10-year treasury rate of the USA. This is, however, not considered as the most appropriate risk-free rate in this thesis due to the investigated period. According to the shorter than ten year period, the definition of the risk-free rate as the 1-year treasury rate of the USA is a more appropriate one. Therefore this is going to be used for the WACC estimation and it amounts to 0.15 %.

The risk-free rate is the base for the cost of debt. The difference between the cost of debt and the risk-free rate is the credit spread of a company. GameStop was affirmed a credit rating of B with stable outlook by Standard and Poor's Ratings Service.[15] Although the credit rating improved, the current category is still indicating that GameStop is operating as a highly speculative firm. Due to this fact the firm has limited excess to capital markets as it falls behind investment grade. The credit spread for companies rated with B amounts to 4.86 %.[16] Therefore the cost of debt for GameStop is 5.01 %.

[15] Data by Capital IQ (FY 2021)
[16] https://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/ratings.htm as 2021

The risk-free rate is also the base for the cost of equity. Additionally, the market risk premium and beta is needed. The market risk premium is a weighted average of the geographical segments. The segments and their weights are the same as for the long-term growth. The risk premium in the US, Canada and Australia is 4.72 %, while it amounts to 5.36 % in Europe. The European risk premium is a weighted average of the equity risk premium of those countries in which GameStop is operating. These are Germany, Austria, Switzerland, France, Italy and Ireland with a risk premium of 4.72%, 5.10 %, 6.85 %, 5.2 %, 4.72 % and 5.54 %, respectively. These premiums are weighted equally.[17] Therefore the weighted average of risk premiums of all geographical segments is 4.82% and this is the equity premium for GameStop.

	WEIGHT	**RISK PREMIUM**
USA	67.14 %	4.72 %
CANADA	5.08 %	4.72 %
AUSTRALIA	12.29 %	4.72 %
EUROPE	15.50 %	5.36 %
EQUITY RISK PREMIUM		**4.82 %**

Table 2: Equity risk premium

Firstly, the basic CAPM model is going to be used for the estimation of the equity risk premium. The market beta is therefore a regression of the monthly returns of GameStop on the S&P 500 index using the last 10 years of historical data. The market beta turns out to be 0.95. That is, the cost of equity – based on the basic CAPM – amounts to 4.73 %.

equity risk premium	4.82 %
beta (market)	0.95
cost of equity	**4.73 %**
cost of debt	**5.01 %**
D/E ratio	-6.75 %
tax rate	20.5 %
WACC (basic)	**4.78 %**

Table 3: WACC (basic) calculation

[17] https://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/ctryprem.html as 2021

As it was stated before the company has $ -1 billion net debt and a current equity value or market capitalization of $ 15 billion furthermore it has a tax rate of 20.5 %. Therefore the D/E ratio amounts to -6.75 %. This results in a WACC of 4.78 % – in case of the basic CAPM. Table 3 summarizes the results.

Secondly, the extended CAPM model is going to be used for the estimation of the equity risk premium. The regression changes to the extent that daily returns of GameStop are regressed on the S&P 500 index and the VIX volatility index using the historical data of the investigated period. The sensitivity for the S&P 500 index is defined as the market beta and VIX sensitivity as volatility beta. These turn out to be 1.94 and 0.32, respectively. The premium for market and volatility are the mean excess returns and amounts to 1.98 % and 0.79 % for market premium and volatility premium, respectively. Therefore applying the extended CAPM results in a cost of equity of 4.27%.

After considering tax, net debt and market capitalization to the same logic as before, the WACC using the extended CAPM amounts to 4.29 %. That is, the use of the extended CAMP model reduces the WACC by 10.25 % (relative terms) and has therefore an important effect on the intrinsic value. The calculation summary is shown in Table 11 in the appendix.

4.2.4. Intrinsic value and sensitivity analysis

In the previous sections the FCFE and the WACC were defined. Firstly, if the WACC is defined with the basic CAPM model and the FCFE is discounted accordingly with the 'basic' WACC the enterprise value of GameStop turns out to be $ 2.79 billion. This leads to an equity valuation of $ 3.8 billion or $ 54.87 per share. Results are shown in Table 12 in the appendix. This valuation is largely dependent on the long-term growth rate and the WACC. Therefore, it is important to accomplish a sensitivity analysis. This is shown in Table 4.

The steps for the sensitivity of the WACC are 0.1 % and thus the range in which the WACC is estimated appears to be between 4.58 % and 4.98 %. The steps for the sensitivity of the long-term growth are 0.25 % and the resulting range is 1.22 % to

2.22%. This sensitivity analysis show that the stock price is estimated to be in the range of $ 47.31 to $ 66.61.

		WACC				
		4.58 %	4.68 %	4.78 %	4.88 %	4.98 %
Growth Rate	1.22 %	51.57	50.41	49.36	48.28	47.31
	1.47 %	54.42	53.09	51.88	50.65	49.53
	1.72 %	57.78	56.21	54.87	53.38	52.10
	1.97 %	61.77	59.92	58.26	56.59	55.09
	2.22 %	66.61	64.37	62.38	60.40	58.63

Table 4: Sensitivity analysis (basic CAPM)

Secondly, if the WACC is defined with the extended CAPM model and the FCFE is discounted accordingly with the ‘extended’ WACC the enterprise value of GameStop turns out to be $ 4.83 billion. This leads to an equity valuation of $ 5.85 billion or $84.35 per share. Results are shown in Table 13 in the appendix. Table 5 shows the sensitivity analysis in the extended model case.

		WACC				
		3.34 %	3.44 %	3.54 %	3.64 %	3.74 %
Growth Rate	1.22 %	75.14	72.26	69.63	67.21	64.99
	1.47 %	83.04	79.39	76.10	73.11	70.38
	1.72 %	93.38	88.60	84.35	80.54	77.11
	1.97 %	107.51	100.95	95.23	90.20	85.74
	2.22 %	127.96	118.36	110.24	103.26	97.21

Table 5: Sensitivity analysis (extended CAPM)

The steps for the sensitivity of the WACC and long-term growth are the same as before. The stock price is therefore estimated to be in the range of $ 64.99 to $ 127.96.

4.3. Valuation with multiples

In this section a different valuation approach is going to be used: the valuation with multiples. The multiple valuation is used as a supplement additionally to the DCF valuation, in order to gain a more precise picture about the valuation fundamentals. This method performs the valuation based on the comparable firms in the industry. It is important to highlight that this valuation considers no meme-effects as it investigates the industry and not whether a stock is a meme-stock or not. Therefore it is relevant for the valuation of GameStop, but less important regarding the investigation of meme valuation, i.e. the key question of this thesis.

In order to perform this valuation method a peer group is needed. There are five companies that fit in the industry: Rent-A-Center Inc. (RCII), Conn's Inc. (CONN), Best Buy Co, Inc. (BBY), Kingfisher plc (KGFHY) and Lithia Motors Inc. (LAD). The first three are computer and electronics retailer, Kingfisher is a home improvement retailer and LAD is an automotive retailer.

Due to the fact that RCII has rather small market capitalization relative to the other companies and additionally its gross margin is much higher than that of the other comparable firms, it is not included in the peer group. Thus the peer group consists of four firms. There is a summary about the key figures in Table 14 in the appendix.

Valuation with multiples are typically using the price earnings ratio (P/E) of the firm being valued. The P/E valuation is, however, not possible in the case of GameStop because the company currently has a negative net income. The next possible multiple is the EV/EBITDA multiple. However, similar to the previous one, GameStop has a negative EBITDA and thus the valuation with this multiple is not possible either.

Therefore the only applicable multiple is the EV/sales. The average EV/sales multiple for the peer group amount to 0.67. Sales of GameStop are $ 5.1 billion and thus the implied enterprise value for the firm turns out to be about $ 3.4 billion. Subtracting net debt, minority interests and pension liabilities result in an equity valuation of $ 4.4 billion or $ 63.55 per share.

average EV / Sales multiple	0.67
GME Sales	$ 5.089.800.000
implied EV for GME	$ 3.384.717.000
minus net debt	$ 1.019.400.000
minus minority interest	-
minus pension liabilities	$ 5.600.000
equity value of GME	$ 4.398.517.000
shares outstanding	69.300.000
implied share price	$ 63.47

Table 5: Multiple analysis

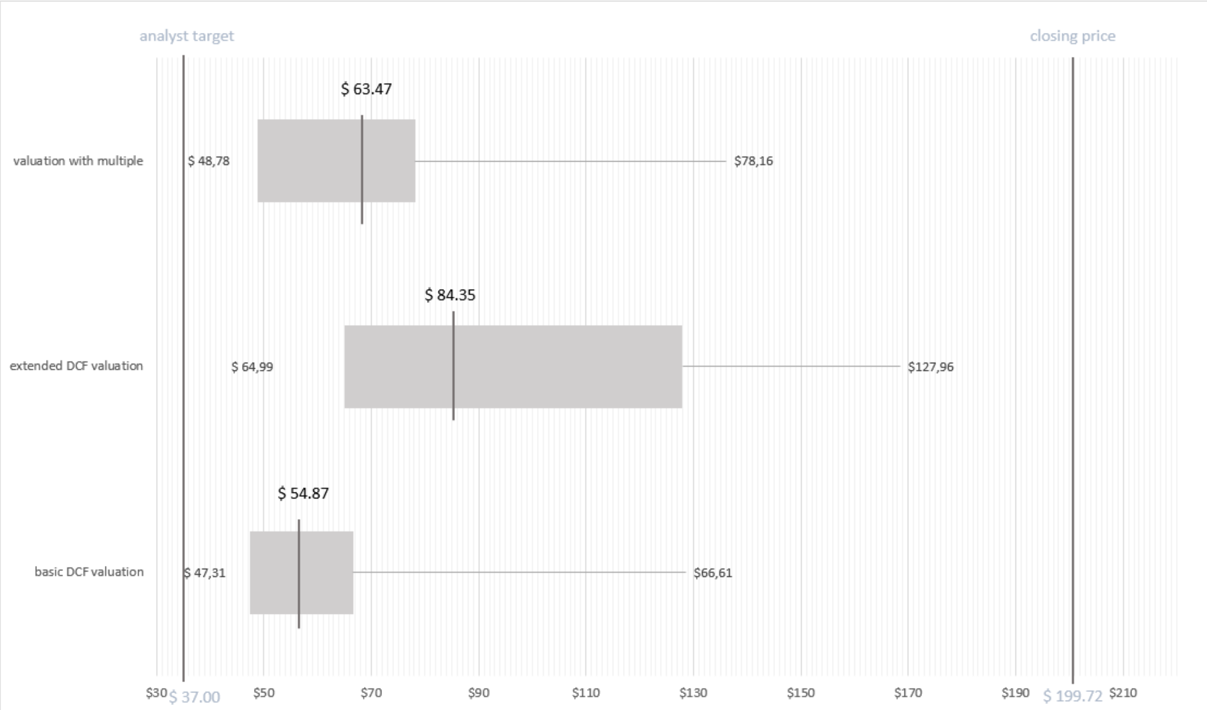
Similarly to the DCF valuation the stock price sensitivity is investigated with respect to the change in the EV/EBITDA multiple. The steps for the change are 0.1 each. This leads to a share price range of $ 48.78 to $ 78.16. The results are shown in Table 15 in the appendix.

4.4. Valuation overview and recommendation

This section summarizes the different valuation methods above. First, the DCF valuation using the basic CAMP model was calculated. The sensitivity analysis resulted in a share price range of $ 47.31 to $ 66.61 and an estimated price of $ 54.87 per share. Second, the DCF valuation using the basic CAMP model was investigated. In this case the range for the price per share turned out to be $ 64.99 to $ 127.96 with the estimated stock price of $ 84.35. Finally, the valuation with multiples leads to a range of $ 48.78 to $ 78.16. The calculated price appears to be $ 63.47 per share.

In addition to these valuation results, there is an analyst price target for GameStop, which amounts to $ 37.00 per share.[18] The closing price at the end of the investigated period is $ 199.72. Graph 1 shows a visual summary of the above discussed valuation results.

[18] Capital IQ data (2022)



Graph 1: Football field

Consequently, this thesis finds an overpricing in both cases – by using the basic as well as the extended model. In case of the fundamental valuation with the basic model the overpricing amounts to 363.99 %, whereas in case of the fundamental valuation with the extended model the overpricing is still 236.76 %. According to this high overpricing the clear recommendation for GameStop stock is to sell.

Concluding, the overpricing due to memes is substantial and it is reasonable to extend the basic CAPM with an additional meme factor – e. g. VIX index – in order to perform a more precise valuation of meme stocks.

Conclusion

This thesis investigates the reason for the large deviation between the price of meme stocks and their fundamentals. This is carried out by following the classical financial perspective, i.e. there must be some unrevealed risk factors in case of the meme stock valuation. These must be responsible for the difference between the actual price and the intrinsic value of a meme stock.

As meme stocks are largely affected by social media influence – which can lead to herding behaviour, greed and fear – developing new models that take such factors into account are of high importance. By testing of possible new models it turns out that the VIX index is a useful additional factor in order to take meme effects into account.

Therefore a new model can be created with a greater explanatory power. Although there are limitations due to the definition of meme stocks and due to the length of the investigation period, the empirical study – applied on GameStop – shows that the extended CAPM, indeed, removes a substantial deviation in price.

In other words, this thesis reveals a risk factor, i.e. herding, which significantly effects the prices of meme stocks. The amount of overpricing declines substantially when the extended CAPM is used instead of the basic model.

However, despite of this extension of the valuation model, there is still a significant remaining overpricing, i.e. fundamental valuation results happens to be much lower than the closing price. Therefore the overpricing could not entirely be explained by the extended model.

Consequently, the extended model should be used with care and the assumptions might be challenged. Also the complexity of the valuation process is increasing as more input factors are required for the extended CAPM than for the basic CAPM.

The fact that many new models turned out to be insignificant – but at the same time the extended model could not entirely explain the overpricing – leads to an important consequence. That is, there must be some other and / or further unrevealed risk factors that can explain the remaining difference between the closing price and the fundamental valuation. In order to find those risk factors further research is necessary.

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II. Links

Definition of meme stocks: https://www.thebalance.com/what-is-a-meme-stock-5118074

TINA: https://www.investopedia.com/terms/t/tina-there-no-alternative.asp

BTD: https://www.investopedia.com/terms/b/buy-the-dips.asp

Definition of VIX index: https://www.cboe.com/tradable_products/vix/

The Wall Street Journal: https://www.wsj.com/livecoverage/amc-gamestop-stock-market/card/FLBEJbdOhyIDnViitKgf

GameStop on Bloomberg: https://www.bloomberg.com/quote/GME:US

Insider: https://www.businessinsider.com/gamestop-worlds-biggest-video-game-retailer-decline-explained-2019-7

GameStop Annual Report: https://news.gamestop.com/static-files/470c5a4c-bb4f-48d4-abec-befd467d3210

Equity premium Statista:

(US) https://www.statista.com/statistics/263614/gross-domestic-product-gdp-growth-rate-in-the-united-states/

(Canada) https://www.statista.com/statistics/263603/gross-domestic-product-gdp-growth-rate-in-canada/

(Australia) https://www.statista.com/statistics/263602/gross-domestic-product-gdp-growth-rate-in-australia/

(Europe) https://www.statista.com/statistics/267898/gross-domestic-product-gdp-growth-in-eu-and-euro-area/

Credit ratings:

https://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/ratings.htm

Credit spreads:

https://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/ctryprem.html

Appendix

I. OLS regressions

```
Call:
lm(formula = dfCoronaDaily$Meme3 ~ dfCoronaDaily$SP500)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.77112 -0.03472 -0.01057  0.02445  0.97211 

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)   
(Intercept)         0.005375   0.005236   1.027  0.30513   
dfCoronaDaily$SP500 0.974073   0.307300   3.170  0.00163 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1123 on 459 degrees of freedom
Multiple R-squared:  0.02142,	Adjusted R-squared:  0.01929 
F-statistic: 10.05 on 1 and 459 DF,  p-value: 0.001628
```

(1): Basic CAPM

```
Call:
lm(formula = dfCoronaDaily$Meme3 ~ dfCoronaDaily$Up5)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.75712 -0.03781 -0.00427  0.02775  0.80105 

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)       0.004836   0.005854   0.826    0.409
dfCoronaDaily$Up5 0.002532   0.013362   0.189    0.850

Residual standard error: 0.1081 on 420 degrees of freedom
Multiple R-squared:  8.546e-05,	Adjusted R-squared:  -0.002295 
F-statistic: 0.03589 on 1 and 420 DF,  p-value: 0.8498
```

(2): Alternative $CAPM_1$

```
Call:
lm(formula = dfCoronaDaily$Meme3 ~ dfCoronaDaily$X3Up0 + dfCoronaDaily$SP500)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.76840 -0.03592 -0.01058  0.02366  0.97482 

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)   
(Intercept)         0.002688   0.007303   0.368  0.71299   
dfCoronaDaily$X3Up0 0.005535   0.010475   0.528  0.59751   
dfCoronaDaily$SP500 0.971754   0.307573   3.159  0.00169 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1124 on 458 degrees of freedom
Multiple R-squared:  0.02202,	Adjusted R-squared:  0.01775 
F-statistic: 5.155 on 2 and 458 DF,  p-value: 0.006107
```

(3): Alternative $CAPM_2$

```
Call:
lm(formula = dfCoronaDaily$Meme3 ~ dfCoronaDaily$VIX)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.75039 -0.03737 -0.00420  0.02865  0.78213 

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)       0.005415   0.005261   1.029    0.304
dfCoronaDaily$VIX 0.043452   0.062083   0.700    0.484

Residual standard error: 0.108 on 420 degrees of freedom
Multiple R-squared:  0.001165,	Adjusted R-squared:  -0.001213 
F-statistic: 0.4899 on 1 and 420 DF,  p-value: 0.4844
```

(4): Alternative $CAPM_3$

```
Call:
lm(formula = dfCoronaDaily$Meme3 ~ dfCoronaDaily$SP500 + dfCoronaDaily$VIX)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.74046 -0.03746 -0.00755  0.02376  0.97835 

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)         0.004558   0.005197   0.877  0.38092    
dfCoronaDaily$SP500 1.871528   0.424841   4.405 1.32e-05 ***
dfCoronaDaily$VIX   0.251175   0.082887   3.030  0.00258 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1113 on 458 degrees of freedom
Multiple R-squared:  0.04066,	Adjusted R-squared:  0.03647 
F-statistic: 9.705 on 2 and 458 DF,  p-value: 7.45e-05
```

(5): Alternative $CAPM_4$


```
Call:
lm(formula = dfCoronaDaily$Meme3 ~ dfCoronaDaily$SP500 + dfCoronaDaily$VIX)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.74046 -0.03746 -0.00755  0.02376  0.97835 

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)         0.004558   0.005197   0.877  0.38092    
dfCoronaDaily$SP500 1.871528   0.424841   4.405 1.32e-05 ***
dfCoronaDaily$VIX   0.251175   0.082887   3.030  0.00258 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1113 on 458 degrees of freedom
Multiple R-squared:  0.04066,	Adjusted R-squared:  0.03647 
F-statistic: 9.705 on 2 and 458 DF,  p-value: 7.45e-05
```


(6): Alternative $CAPM_5$

```
Call:
lm(formula = dfCoronaDaily$Meme3 ~ dfCoronaDaily$SP500 + dfCoronaDaily$SP500.2 +
    dfCoronaDaily$VIX + dfCoronaDaily$VIX.2)

Residuals:
     Min       1Q   Median       3Q      Max
-0.75723 -0.03681 -0.00767  0.02675  0.97774

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)             0.004161   0.005678   0.733   0.4641
dfCoronaDaily$SP500     1.780356   0.425495   4.184 3.43e-05 ***
dfCoronaDaily$SP500.2 -12.080980   5.159666  -2.341   0.0196 *
dfCoronaDaily$VIX       0.214644   0.089740   2.392   0.0172 *
dfCoronaDaily$VIX.2     0.519371   0.340293   1.526   0.1276
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1109 on 456 degrees of freedom
Multiple R-squared:  0.05264,   Adjusted R-squared:  0.04433
F-statistic: 6.335 on 4 and 456 DF,  p-value: 5.745e-05
```

(7): Alternative CAPM$_6$

```
Call:
lm(formula = dfCoronaDaily$Meme3 ~ dfCoronaDaily$SP500.2 + dfCoronaDaily$SP500 +
    dfCoronaDaily$VIX)

Residuals:
     Min       1Q   Median       3Q      Max
-0.73749 -0.03804 -0.00878  0.02555  0.97803

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)            0.007067   0.005357   1.319  0.18776
dfCoronaDaily$SP500.2 -8.559526   4.621757  -1.852  0.06467 .
dfCoronaDaily$SP500    1.788565   0.426080   4.198 3.24e-05 ***
dfCoronaDaily$VIX      0.266803   0.083098   3.211  0.00142 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.111 on 457 degrees of freedom
Multiple R-squared:  0.0478,    Adjusted R-squared:  0.04155
F-statistic: 7.647 on 3 and 457 DF,  p-value: 5.361e-05
```

(8): Extended CAPM (alternative CAPM$_7$)

II. Calculations

[IN TSD]	2017 FY	2018 FY	2019 FY	2020 FY	2021 FY
UNITED STATES	5 660 000	5 876 000	5 800 200	4 497 700	3 417 100
REV. GROWTH		3,8%	-1,3%	-22,5%	-24,0%
CANADA	382 000	434 900	434 500	344 200	258 400
REV. GROWTH		13,8%	-0,1%	-20,8%	-24,9%
AUSTRALIA	609 500	702 200	645 400	525 400	625 300
REV. GROWTH		15,2%	-8,1%	-18,6%	19,0%
UNITED STATES	5 660 000	5 876 000	5 800 200	4 497 700	3 417 100
EUROPE	1 313 500	1 534 000	1 405 200	1 098 700	789 000
REV. GROWTH		16,8%	-8,4%	-21,8%	-28,2%
TOTAL	**7 965 000**	**8 547 100**	**8 285 300**	**6 466 000**	**5 089 800**
REV GROWTH		**7,3%**	**-3,1%**	**-22,0%**	**-21,3%**

Table 6: Sales in previous years

[IN TSD]	2022E	2023E	2024E	2025E
UNITED STATES	3 677 910	3 888 448	4 111 038	4 424 813
REV. GROWTH	7,6%	5,7%	5,7%	7,6%
CANADA	294 184	324 738	358 466	408 107
REV. GROWTH	13,8%	10,4%	10,4%	13,8%
AUSTRALIA	720 403	802 579	894 128	1 030 118
REV. GROWTH	15,2%	11,4%	11,4%	15,2%
EUROPE	921 451	998 794	1 082 629	1 264 372
REV. GROWTH	16,8%	8,4%	8,4%	16,8%
TOTAL	**5 613 948**	**6 014 559**	**6 446 260**	**7 127 409**
REV GROWTH	**10,3%**	**7,1%**	**7,2%**	**10,6%**

Table 7: Sales Growth Estimation

[IN TSD $]	2022E	2023E	2024E	2025E
REV. GROWTH	10.3%	7.1%	7.2%	10.6%
REVENUE	5 613 948	6 014 559	6 446 260	7 127 409
COGS	4 053 335	4 361 740	4 680 892	5 213 510
GROSS PROFIT	1 560 613	1 652 819	1 765 369	1 913 899
GROSS PROFIT MARGIN	**28%**	**27%**	**27%**	**27%**
SELLING EXPENSES	1 608 037	1 632 568	1 653 053	1 720 813
SELLING EXP. / SALES	29%	27%	26%	24%
OPERATING INCOME	**(47 424)**	**20 251**	**112 315**	**193 086**
OPERATING MARGIN	**-0,8%**	**0,3%**	**1,7%**	**2,7%**

Table 8: Forecasting important items

YEAR	2022E	2023E	2024E	2025E
PERIOD	1	2	3	4
EBIT [IN TSD $]	(47 424)	20 251	112 315	193 086
NOPAT [IN TSD $]	(37 707)	16 102	89 303	153 525
DEPRECIATION [IN TSD $]	6 186	6 628	7 104	7 854
CAPEX [IN TSD $]	7 500	8 035	8 612	9 522
CHANGE IN NWC [IN TSD $]	(105 299)	31 149	33 566	52 961
FCFE [IN TSD $]	**66 278**	**(16 454)**	**54 229**	**98 895**

Table 9: FCFE estimation

YEAR	2022E	2023E	2024E	2025E
ACCOUNTS RECEIVABLE	168 238	180 244	193 181	213 594
% OF SALES	3,0%	3,0%	3,0%	3,0%
INVENTORY	769 875	824 813	884 015	977 425
% OF SALES	13,7%	13,7%	13,7%	13,7%
ACCOUNTS PAYABLE	501 612	537 407	575 980	636 842
% OF SALES	8,9%	8,9%	8,9%	8,9%
NWC	436 501	467 650	501 216	554 177
CHANGE IN NWC	**(105 299)**	**31 149**	**33 566**	**52 961**

Table 10: Change of net Working Capital [in TSD $]

equity risk premium	1.98 %
beta (market)	1.79
beta (market^2)	-8.56
beta (volatility)	0.27
volatility risk premium	0.79 %
cost of equity	3.57 %
WACC (extended)	3.54 %

Table 11: WACC (extended) calculation

Terminal value [in TSD$]	3 296 966
Enterprise value	2 788 448
Minus Net Debt	(1 019 400)
Minus Minority interest	-
Minus Pension Liabilities	5 600
Equity value (Market Cap)	3 802 248
Shares outstanding	69 300
Price per share	54.87

Table 12: DCF (basic)

Terminal value [in TSD$]	5 532 026
Enterprise value	4 831 630
Minus Net Debt	(1 019 400)
Minus Minority interest	-
Minus Pension Liabilities	5 600
Equity value (Market Cap)	5 845 430
Shares outstanding	69 300
Price per share	84.35

Table 13: DCF (extended)

	CONN'S INC	BEST BUY CO, INC	KINGFISHER PLC	LITHIA MOTORS INC
INDUSTRY	Computer & Electronics Retail	Computer & Electronics Retail	Home Improvement Retail	Automotive Retail
MARKET CAP	675,04M	24,07B	9,30B	9,30B
EV / SALES	**0.98**	**0.47**	**0.56**	**0.65**

Table 14: Peers

		share price
EV / Sales	0.47	48.78
	0.57	56.13
	0.67	63.47
	0.77	70.82
	0.87	78.16

Table 15: Sensitivity analysis (multiples)