Factors explaining the performance of the listed food and drink industry stocks during the covid-19 pandemic

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FACTORS EXPLAINING THE PERFORMANCE OF THE LISTED FOOD AND DRINK INDUSTRY STOCKS DURING THE COVID-19 PANDEMIC

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1. Introduction

Since years, active investors have searched which stock or which sector might be able to outperform the market in the short or long term based on its past performance. Similarly, these active investors reacted to changing financials market conditions by changing their asset allocation and rotating their portfolio of securities between different types of securities or sectors to benefit from their particular behavior with regards to certain market conditions (Sassetti et al., 2003). Hence, active investors tend to prefer affecting a part of their portfolio towards safe-haven investments such as defensive stocks when they anticipate or think they are experiencing a period of financial market distress (Davis & Phillips, 2007). Thanks to these defensive stocks, active investors try to reduce the volatility of their portfolio with regards to the market. By reducing their portfolio volatility these investors try to reduce the decrease in their portfolio value that might be caused by the particular economic conditions.

Defensive stocks are qualitatively defined as stocks from firm that produce goods or services with relatively inelastic demand curves. Then, from a more quantitative aspect defensive stocks can be identified as stocks with a beta of less than one (meaning they are experiencing less volatility than the market portfolio. Previous studies have also shown that stocks coming from defensive sectors tend to have even reduced beta in times of financial distress such as bear market or recessions (Ole-Meiludie et al., 2014).

Among these sectors that are considered as defensive is the food and drink industry, this industry is stable and usually considered as more resistant to economic cycles and fluctuations than other industries (Šimáková et al., 2019). Indeed, most of the food and drinks industry goods exhibit a strong pricing-power combined with a stable demand and hence are good examples of the qualitative definition of defensive stocks. Historically, during the last global financial crisis linked to the subprimes in 2008, the food and drink industry sector experienced the lowest decrease in value among the sectoral indices reported by STOXX600 Europe (Šimáková et al., 2019).

During the covid-19 pandemic period of financial distress, the decline in the food and drink industry was much lower compared to total manufacturing production decline. However, the impact on the different companies from the industry was substantially different between sub-sectors. The packaged and frozen foods companies as well as the food retailers faced a steep increase in sales, while HORECA[1] linked companies were hit the hardest from the consumer behavior drastic shift imposed by the sanitary situation (Maarten VET et al., 2021).

This unprecedented situation allows to study with brand new data the different factors explaining the performance of the listed food and drinks industry stocks during the covid-19 pandemic.

Defensive stocks characteristics, their behavior while facing different types of financial markets or economic conditions, what are the sectors that can be considered as defensive and the results from defensive equity investing based in the low volatility anomaly through the years have already been discussed in the financial literature (Collie & Osborn, 2011; Blitz & van Vliet, 2007). Many papers also cover the changes in the asset allocation to shift towards more defensive stocks and although several studies certify that in theory modifying the asset allocation by rotating between different sectors in reaction to certain financial indicators allow to consistently outperform the market (Sassetti et al., 2003), these results are usually mitigated by their modest efficiency in practical situations due to the low reliability of the factors triggering the shift in asset allocation (Davis & Phillips, 2007).

[1] HORECA is an acronym used to refer to the businesses linked to hotels, restaurants and caterings.

Identification of stocks behavior to try to understand which of them might outperform the market portfolio in the future has also already been studied with different multi factor models based on the arbitrage pricing theory (APT) such as the Fama and French factor models or even models using fundamental investment indicators like the Piotroski F score (Piotroski, 2000) and (Hyde, 2018).

However, studies concerning the factors that explain past performance and might explain future outperformance of food and drinks industry stocks has not yet been done. The purpose of this thesis is to try to determine which financial indicators or factors are relevant and should be considered to identify future outperformers among the food and drink industry stocks in times of financial distress using explanation of their past returns coming from the Covid-19 pandemic linked period of financial distress.

To do so, this thesis will analyze the daily prices of the European-Union food and drinks industry stocks with regards to several companies' indicators via a principal component analysis in order to determine which indicators form the more relevant risk factors to explain the results of these companies during the covid-19 period. These factors will then be tested in a Fama-Macbeth regression to asses if they have significantly explained the returns of the stocks during the covid-19 crisis period.

This thesis is divided as follow, first the literature review and the theoretical framework about the risk return tradeoff, defensive equity characteristics, asset pricing theory and multiple factor models will be covered in the section 2. Then, the methodology employed to try to identify factors explaining the performance of the European food and drinks industry stocks will be presented as well as the data selection process in section 3. Furthermore, the statistical results of the principal component analysis and the Fama-Macbeth regression will be laid out in section 4 and interpreted in depth in section 5. Eventually, final remarks and conclusion will be given in section 6.

2. Literature review and theoretical framework

In this section, several topics are addressed to lay out the state of academic research concerning defensive equities and the potential characteristics explaining their returns as well as the different existing models explaining stock returns.

2.1 Investment risk return tradeoff, beta and CAPM

Based on traditional finance theory, investors are risk averse rational individuals seeking to maximize their returns according to their investment constraints and the level of risk they are willing to accept. These assumptions laid the ground to the Modern Portfolio Theory (MPT) and the Tobin Separation Theorem developed by Markowitz (1952) and Tobin (1958). In its paper, Markowitz first showed the effect of diversification by proving that the risk of a portfolio[2] is lower than the weighted sum of its individual securities variance and by doing so highlight the possibility of finding optimal weights for the different assets in order to have the best risk adjusted return. Later in the Tobin paper, the second basis of the Modern Portfolio Theory was developed with the addition of a risk-free asset in the potential combination of securities allowing the development of the capital allocation line (CAL) that will be discussed later in this section. The Modern Portfolio Theory (MPT) is mainly based on the assumption that investors are risk averse and therefore will always for a given level of expected return prefer the less risky portfolio and for a given level of risk prefer the portfolio with the highest expected return. Consequently, an investor should be compensated for an investment involving a higher level of risk by a higher expected return.

In his paper, Markowitz uses the standard deviation as a measure of the portfolio level of risk, this portfolio standard deviation relies on each of the portfolio stock standard deviation[3], the weight of each stock in the portfolio and the correlation between them. However, by proving the effect of diversification and due to the incapacity of standard deviation to consider this diversification effect, a more representative measure of risk was later proposed: beta.

The beta of a stock measures how much investors are willing to pay for this security's market risk. It is a measure of the stock's systematic risk[4]. The beta of a stock compares the volatility of the stock returns with the volatility of the market portfolio returns to determine the stock sensibility to the overall market macroeconomic factors. Therefore, the addition of a stock with a beta lower than one (less volatile than the market portfolio) in a portfolio will decrease this portfolio level of systematic risk while the addition of a stock with a beta greater than one (more volatile than the market portfolio) in a portfolio will increase this portfolio level of systematic risk. Furthermore, a stock with a negative beta is negatively correlated with the market portfolio and would therefore evolve in the opposite way of the market, meaning that this stock will go up in value when the market value goes down and inversely.

This risk-reward relation from the modern portfolio theory led to the creation of the Capital Asset Pricing Model (CAPM) by William Sharpe (1964). In the CAPM the risk-reward relation is depicted by the CAL, the red line (Figure 1) Shows what should be the expected return of the portfolio for a given level of beta starting from the risk-free rate[5] in order to keep the risk return tradeoff (here measured

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[2] Here measured by its standard deviation

[3] The standard deviation is a volatility measure showing how distant the group members values are from the group mean value. In finance this mathematical measure is commonly used to determine how widely spread out the stock value have been over time and so how risky they are.

[4] The systematic risk of a stock refers to the non-diversifiable risk of fluctuation of the stock value due to macroeconomic factors

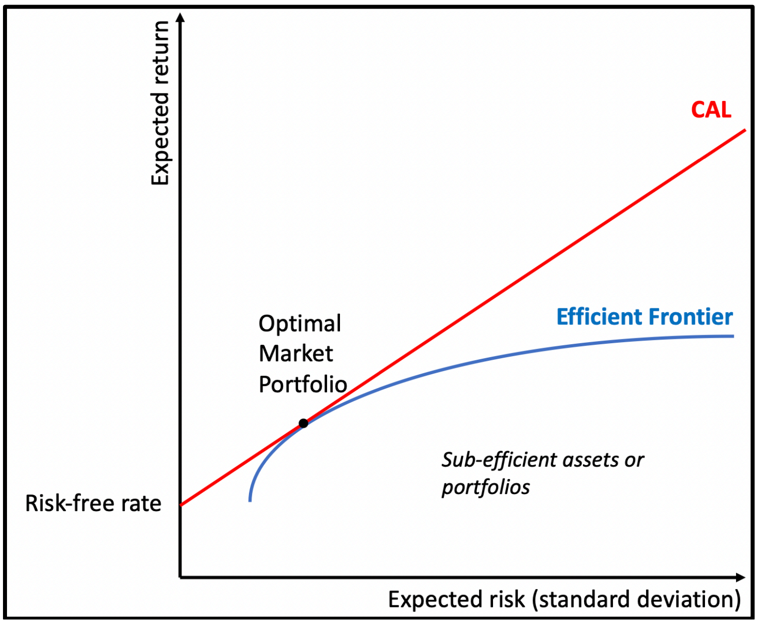
[5] The risk-free rate is the rate of return an investor can expect to obtain on an investment carrying zero risk.

with the Sharpe ratio[6]). The slope of the line is usually determined by the reward-risk ratio considered as needed. In terms of efficiency the steeper the slope of this line and the most efficient (in terms of risk adjusted return) the combination is.

Another notion defined in the MPT is the Efficient Frontier, this frontier is the combination of stocks yielding the highest expected return for each level of beta. This efficient frontier is represented as the blue curve in Figure 1. This curve shows the optimal diversification level that can be reached with different weighting of the securities.

According to the constraints from the efficient frontier, the best CAL is the one which is tangent to the efficient frontier I.e., the one with the steeper slope). The intersection between the Capital Allocation Line and the Efficient Frontier is determining the theoretical Optimal Market Portfolio. This portfolio is the one which should offer the best risk-reward tradeoff, that is the best Sharpe ratio[7] between the risky stocks that are investable for the investor and a risk-free asset (the risk-free asset being an asset with zero risk). This theoretical Optimal Market Portfolio is the one that we are considering while talking about market portfolio or market return in the following of this literature review. In order to seek for higher returns while keeping the same risk return tradeoff past the Optimal market Portfolio an investor would have to borrow money and use leverage.

Figure 1: Modern Portfolio Theory representation



The CAPM defines the following linear relationship between the stock expected return and its beta:

$$\mathrm{ER_i} = \mathrm{R_f} + \beta_\mathrm{i} * (\mathrm{ER_m} - \mathrm{R_f})$$

Where:

- $\mathrm{ER_i}$ is the expected return for the stock i
- $\mathrm{R_f}$ is the risk free-rate (rate of return for the risk-free asset)
- β_i is the beta of the stock i
- $\mathrm{ER_m}$ is the expected return for the market portfolio

[6] The Sharpe ratio is a risk-adjusted measure of return developed by William Sharpe in 1994 (Sharpe, 1994).
[7] The Sharpe ratio is a risk-adjusted measure of performance computed as the difference between a portfolio returns and the risk-free rate, divided by the standard deviation of this portfolio excess returns (Sharpe 1994).

In conclusion the Modern Portfolio Theory states that investors are risk averse and in order to try to maximize their returns they should identify their Capital Asset Allocation line according to their risk level (here characterized by the volatility of the returns compared to the market) and should follow it in order to benefit from the best risk-adjusted returns available for them. Investors taking on risk expect in general to be paid more for bearing this risk, because of their risk aversion. Investors should choose an investment with a higher level of risk only if they expect to be positively rewarded for taking additional risk. In the absence of this expectation, all investors would avoid this riskier investment, this situation would affect the supply and the demand for this asset and re-equilibrate its price to a level exhibiting an adequate risk premium. As Mottogrotto (2017) emphasizes, based on the CAPM, the beta of a stock is the only stock-related determinant of its return.

However, in practice some risk averse investors might be tempted to seek for higher returns by following the part of the Efficient Frontier on the right of the optimal market Portfolio (thus accepting a lower risk adjusted return) for various reasons that will be discussed more in depth later in the proper section.

2.2 Investment risk measures

In finance risk can be qualitatively defined as the probability that an investment real return differs from its expected return and that includes the possibility of losing part or all of the invested amount. From a quantitative point however, the definition and measurement of risk can take different forms among which: the volatility of the stock returns, the beta regarding the market portfolio[8], the idiosyncratic risk[9], the tracking error[10], the financial leverage or even the earnings stability.

Problems can arise from the fact that different investors can use different risk measures and more particularly from the fact that too much investors still considers tracking error as their only measure of risk. This might lead investors to consider some assets as non-risky despite them being considered risky while using other risk measures such as the volatility of their stock returns alone. Inversely some low-risk stocks might behave in a different manner from the broad market and then exert a high tracking error despite having a low level of volatility of their returns compared to the benchmark. This mismatch in investment risk measure among the investors might create opportunities for defensive investing strategies that are discussed later in this section.

2.3 Defensive equity

The qualitative definition of defensive stocks usually refers to stocks that are exposed to a lesser degree to the cyclical behavior of the economy and the financial markets (experiencing phases of growth and recession). In both these phases these defensive stocks are expected to react in a lesser extent with regards to the market as a whole. This is the result of these stocks businesses experiencing a nearly inelastic demand curve (with regards to the price) for the goods and services that they produce as they are considered as essential regardless of the current economic conditions (Davis & Phillips, 2007). Defensive stocks are characterized by low sales and earnings volatility as well as low business risk because their products and services are less affected by the current state of the economy in opposition to cyclical stocks that exert opposite characteristics.

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[8] The beta of a stock regarding the market portfolio is a measure of the volatility of the stock returns in comparison with the volatility of the returns from the whole market.
[9] The idiosyncratic risk of a stock is the part of the stock's risk that is inherent to this particular stock and that can be eliminated by a diversification inside a large portfolio of securities.
[10] The tracking error measures the divergence between an investment's price behavior and the price behavior of the benchmark. It is measured as the standard deviation of the difference between the investment's return and the benchmark return.

Over time defensive sectors have been defined within the GICS[11] sectors classification (using their sector average volatility of the returns). These sectors are: consumer staples, energy, healthcare, telecommunication services and utilities. However, this sector classification is made from sector average and does not guarantee that a stock from these sectors will always be defensive as some stock from these sectors can exert some characteristics from a cyclical stock and vice-versa. Another definition has been proposed by Adrian Asinas (2018) using earnings variability[12] it has not proven statistically significant. The food and drinks industry stocks used in this thesis are part of the consumer staples broader sector. This industry exhibits indeed a nearly inelastic demand curve (with regards to the price) as these products will be bought and consumers will consume them regardless of the state of the economy. Defensive equities are also generally characterized by some fundamental measures of low risk also called "quality indicators" (these reflect the stock sensitivity to its economic environment), these fundamental ratios characteristics of defensive equity are high profit margins, low financial and operating leverage and lower earnings volatility than the market.

The quantitative definition of defensive sectors usually refers to the beta of these industry being low. The exact threshold below which a stock can be considered as defensive varies across the studies, it is generally assumed to be 1 but some studies such as Adrian Asinas (2018) advocate the use of a 0.7 threshold or the use of a mean asset beta threshold between 0.6 and 0.8 according to the company business sector. This beta inferior to one reflects their low level of correlation with the market portfolio and their level of returns volatility lower than those of the market. Some studies have even shown that the beta of these defensive sectors tends to decrease as the horizon of their measurement increase (Levy, 1984). This beta lower than one and therefore the lower level of volatility in the stock returns is viewed by a majority of investors as a downside protection in times of financial distress, in other words these sectors are expected to see a smaller decline in their value than other sectors in times of bad economic conditions.

Defensive stocks and defensive sectors have been proven to exert particular characteristics. Ole-Meiludie et al in their 2014 paper demonstrate that one can expect defensive stocks to remain non-cyclical both in times of recession and bear market. Moreover, as value stocks tend to be more stable than growth stocks, one would be tempted to categorize them as defensive stocks or at least expect that the price to book ratio (P/B) of a stock (as it is what differentiates value stocks and growth stocks) would be a characteristic considered to identify this stock as defensive. However, this is not the case. In fact, defensive stocks also share characteristics with growth stocks such as higher P/B ratios or higher return on assets. Ole-Meiludie et al also related this phenomenon in their study as they demonstrate that the beta of defensive companies tends to be lower as the market capitalization is lower (at least on the study conducted on the Johannesburg stock exchange). This can go against the general belief that a bigger company might be more able to navigate market and economic downturn trough their economies of scale. Another observation from this paper is that stocks cyclical or non-cyclical characteristics tend to be exacerbated in times of market crisis compared to times of recession, meaning that a stock considered as aggressive (with a beta bigger than one) would become even more aggressive during a market crisis (the stock would have an increased beta) and a stock considered as defensive (with a beta lower than one and bigger than zero) would become even more defensive during a market crisis (it would have a beta closer to zero).

Thanks to their low correlation with the market, defensive stocks are expected to outperform the market in times of financial distress but to underperform the market in times of bull markets and

[11] GICS or Global Industry Classification Standard refers to a method developed by S&P Dow Jones indices and MSCI to class stocks into sub-industry, industry, industry group and sectors according to the company's primary business activities (business activities that generate the majority of the company revenues).

[12] more precisely quarterly sector earnings correlation to quarterly earnings from the benchmark

economic boom. Davis & Phillips (2007) defines defensive stocks as a form of insurance against large drawdowns and big loss, the assurance premium being the possibility to miss some profits when the financial markets revert from a negative to a positive trend. Frazzini et al. (2012) confirm that historically (on a period from 1984 to 2011 in the US markets) defensive stocks have experienced smaller drawdowns than the broad market and have recovered to their previous level faster than the broad market.

2.4 Defensive equity investing and the low volatility anomaly

According to Collie & Osborn (2011), defensive equity investing offers the possibility of a reduction in portfolio risk (reduction of the returns volatility) and a more attractive tradeoff between risk and return. The objective of defensive stocks investing strategy is to reduce the investments returns sensitivity to the market in order to obtain benchmark-like returns with a lower volatility level in the long-term.

According to the Modern Portfolio Theory, riskier stocks should lead to higher expected return due to their risk premium and thus investments in these should provide higher returns over the long run than the market. However, the scientific literature has already proven that there are anomalies that reduce the risk premium and thus riskier investments' returns over time. Fama and French in the abstract of their 1992 paper emphasize the fact that when the test allows for variation in market beta unrelated to size the relation between the average return and the market beta is flat even in the case of the market beta being the only explanatory variable and that the market beta seems to have no role in explaining the average returns of stocks on the New York Stock Exchange, the American Stock Exchange and the Nasdaq between 1963 and 1990. Blitz & van Vliet (2007) demonstrate that there is a negative relation between returns and increasing risk (by looking at both the volatility of returns and the betas) over the period from 1986 to 2006 regardless of the market and the level of economic development. Baker et al (2011) arrived at the same conclusions that historically higher risk has been associated with lower returns on average.

The mispricing of the risk premium allows investors to create a better asset allocation targeting the same expected return with less risk (or lower volatility of the returns) this mispricing allowing defensive equity to generate higher risk-adjusted returns than riskier stocks is referred to in the financial literature as the low volatility anomaly or low beta anomaly. The low volatility anomaly expresses the observation that historically, low volatility stocks have had higher returns than high volatility stocks regardless of the market. This phenomenon is proven true in several financial research (Frazzini et al., 2012; Collie & Osborn, 2011; Adrian Asinas, 2018; Novy-Marx, 2014; Baker et al., 2011; Blitz & van Vliet, 2007) and several strategies try to benefit from it by overweighting defensive or safer stocks and underweighting risky stocks (low beta, minimum variance, low volatility or defensive equity strategies). These strategies exert higher risk adjusted performance than the market benchmarks when back tested, as average return of high-beta stock has been about the same than the average return of low-beta stocks within the same asset class. However, low-beta stocks returns have been less volatile (when comparing compound returns the high-beta stocks returns where even lower than the low-beta stocks returns).

Previous researchers have identified some potential explanations for the low volatility anomaly. According to Baker et al (2011) a widely spread use of tracking error as the sole risk measure by mutual funds and asset managers could explain the low volatility anomaly. The use of tracking error could lead to a preference for more cyclical stocks as they tend to behave in the same way as the market, while defensive stocks behaving in a different way than the market might exert higher tracking error.
This preference for high-beta stocks from many investors could have an impact on their prices and hence decrease their risk premium. Moreover, if the tracking error is the only used risk measure the benefit of a defensive equity investing strategy would not be easily noticeable as the strategy put the

emphasis on reducing the volatility of the returns. It should be noted that the tracking error does not consider the volatility of the returns and as a consequence the tracking error will not be visible in the investment management reports. One solution to this phenomenon would be to continue to highlight the need for more risk measures and risk-adjusted returns metrics in investment management, and particularly measures that consider the absolute risk (volatility of returns) such as the Sharpe ratio. A second solution to this phenomenon would be to use more defensive indices to benchmark defensive equity strategies when using tracking error.

Baker et al (2011) propose another potential explanation i.e., that the incentive for investment managers to take more risks while seeking for higher returns even if the overall risk-adjusted return level is reduced. As of today, most of the money managed in financial markets is professionally handled by mutual funds or institutional investment accounts and the main objective of these type of investors is to beat their benchmark, so they have no particular incentive to prefer low-risk stocks. Rather, this situation creates an incentive for these investors to take a riskier approach in order to be the fund that has outperformed the market rather than staying among the average fund returns. Collie & Osborn (2011) stated that it is much more interesting to be among the top performers than being an average fund as bonuses can be very significant in the event of a large success (through the performance fees). These performance fees cannot be clawed back in case of future underperformance for many mutual funds, these funds hence benefit from an asymmetric reward system. This effect is even reinforced by the professional investment managers confidence in their stock picking skills further strengthening the incentive to select riskier stocks for their higher expected return.

Black (1972) proposes one additional potential explanation, the investors leverage aversion or leverage constraints. According to the modern portfolio theory developed by Markowitz (1952) and the Tobin separation theorem developed by Tobin (1958), in the CAPM model, once the tangency portfolio point has been reached (tangency point between the CAL and the efficient frontier), in order to seek for higher returns while maintaining the same risk-return tradeoff (same Sharpe ratio) the investor should use borrowed money to leverage. However, an anomaly seems to come from the fact that some investors are not only risk averse but also exert a strong leverage aversion or leverage incapacity (some mutual funds are prohibited from borrowing as an example). This inability or unwillingness to borrow can push them to overweight risky securities in their portfolio to seek for higher returns (moving along the right side of the efficient frontier instead of the CAL) while accepting to degrade their risk return tradeoff. One empirical evidence for this phenomenon is that low-beta portfolios returns tend to be correlated with the credit market conditions (accessibility of borrowings).

As the success of defensive equity investing strategies has been proven over time, some investors might be tempted to try benefiting from the best of both worlds by investing in cyclical stocks when the financial markets seem to be in an upward trend and investing in defensive stocks when the financial markets seem to be in a downward trend. Sassetti et al (2003) studied the impact of using systematic sector rotation on the returns, and showed that between January 1998 and September 2003 on the US market (a period containing a full economic cycle with two bull markets and one bear market) a dynamic switch between different sector of stocks based on sectors momentum would have yield better return than a passive or semi-passive strategy (better return than the S&P500 over the same period). This study could comfort investors in the belief that shifting from defensive sectors to cyclical sectors at the right time could yield better results than simply investing in the market portfolio. However, despite the fact that this kind of strategies seems to work when being back tested. Ole-Meiludie et a, (2014), Davis & Phillips (2007) and Yelamanchili (2019) show that in practice, results of strategies shifting to defensive stocks in times of financial distress are generally mitigated by the difficulty to effectively foresee these times of financial distress and therefore to apply the sector shift on time. Several indicators are generally considered as predictors to foresee imminent financial downturns such as:

- a 12-month market returns drop of at least 5% (supposed to be a signal highlighting the fact that the current economic downward trend goes forward and that economy will enter a recession and market become bear markets),

- a current price to earnings ratio (P/E) that is at least two standards deviation above the historical forward P/E (supposed to be a signal highlighting a potential markets overvaluation and a potential nearby decline to reequilibrate),

- an inverted yield curve, commonly a negative difference between the 10-year maturity yield and the 3-month maturity yield (supposed to be a signal highlighting the fact that short term is priced as riskier than long term and that there is a strong demand for long-term fixed income instruments driving their prices up and their yields down). This inverted yield curve is the direct consequence of the strong demand for long-term fixed income instruments and reflect investors uncertainty about the near-term economic future This signal is commonly considered as the best signal to predict a recession.

Unfortunately, all these signals have been proven to exert a statistically insignificant predictive power because of lots of fake positives (presences of the signals that were not followed by recessions or bear markets) and fake negatives (presence of recessions or bear markets although there was no signal). This poor predictive power prevents sectors rotation strategy between cyclical and defensive sectors to work properly in practice.

At present, the efficiency of defensive equity investing strategies and the low volatility anomaly have been addressed in the previous subsections. Nevertheless, the potential factors explaining the defensive stocks behavior and results have not yet been extensively addressed.

2.5 The particular case of food and drinks industry during the covid-19 crisis

Although the food and drinks industry is commonly considered as a defensive industry and has proven to be defensive in the past, the covid-19 crisis has had a particular impact on this sector (Maarten VET et al., 2021; Aday & Aday, 2020; Plata et al., 2022).

According to Maarten VET et al (2021), the first and second waves of contaminations from the covid in Europe and more particularly the lockdowns following the rising number of infections had very diverse impact on food and drinks industry firms depending of the firm level of proximity to the HORECA sub-sector. Firm linked to the HORECA sub-sector were hit the hardest by the lockdowns restrictions (preventing them to run their businesses as usual) while the food retailers' sub-sector (particularly the retailer of frozen and packaged foods) benefited from increase in their sales as a compensation to the customers inaccessibility to the HORECA sub-sector but also due to movements of panic buying and stockpiling. The food sector was not the only one impacted by a change in the consumption behavior as the alcoholic beverages drinks sub-sector was also impacted by the covid-19 related lockdowns , during the whole length of the covid-19 crisis the consumption of alcoholic beverages slightly decreased in comparison with previous years (Plata et al., 2022).

These shifts in the consumption habits combined with partially closed borders (distorting supply for inputs), panic buying, stockpiling and lockdowns workforce shortages (soothed by the "essentials" worker status) triggered a risk of supply chain issues for the food and drinks industry in Europe. Fortunately, the European food and drinks supply chains have remained resilient (Maarten VET et al., 2021), (Aday & Aday, 2020).

All these diverse and unprecedented impacts the covid-19 crisis caused on the sector due to its particular pandemic characteristic could have impacted the defensive characteristic of the sector. However, according to Maarten VET et al (2021), the decline in the sector production was lower than the decline in the broad market. This same observation has been held true for the development turnover and the employment levels. These results corroborate the defensive assumptions of inelastic demand curve for products judged as essentials and these firms reacting to a lesser extent in comparison with the market. Even if some of the sector firms have experienced bad returns during the crisis, the general sector trend appeared to have remained defensive.

2.6 Arbitrage pricing theory

The Arbitrage Pricing Theory (APT) is the main successor of the CAPM and was introduced by Ross (1976) this theory suggests that the CAPM beta is not sufficient and that a small number of systemic factors (economic variables or factors) are better suited for explaining stocks long-term returns. As the Institute of Chartered Financial Analysts. Research Foundation (1994) reiterates, this theory highlights the fact that even the best diversified portfolios are not risk free as there are common economic forces that can pervasively influence all the portfolio stocks' returns and so there are still risks that cannot be eliminated by diversification (systemic risks). The APT seeks to explain the stocks expected returns by representing them as a linear combination of the systemic factors (or systematic risks). The model tries to capture and explain the relationship between a stock return and the risk inherent to the systemic factors by estimating the variation in the return explained by each of the systemic factors. According to these systemic factors, stocks with the same CAPM beta could react in different ways one from another to some macroeconomic events due to the difference in exposure (APT betas) to the different systemic factors. The APT general equation can be written as:

$$\mathrm{ER_i} = \mathrm{R_f} + (\beta_{1i} * f_1) + (\beta_{2i} * f_2) + \cdots + (\beta_{ni} * f_n)$$

Where:

- $\mathrm{ER_i}$ is the expected return for the stock i
- $\mathrm{R_f}$ is the risk-free rate
- β_{1i}, β_{2i}, …, β_{ni} are the betas of stock i regarding the factors 1,2, … and i
- f_1, f_2, …, f_n are the systemic factors explaining the stock returns

Over the years, APT has become a field of study using computational and statistical models to analyze and a lesser extend predict financial assets behavior. One main limitation from the Arbitrage Pricing Theory is that the theory does not define a set of factors and supposes instead that the systemic factors affecting the stock returns are known by the investor. As APT highlights the existence of unidentified factors that can be used to explain stock returns, the theory has led to the development of several multi-factors models over the years.

2.7 Multiple factors models and additional explanations of stock returns

Following the Arbitrage Pricing Theory, several papers identified anomalies in the financial markets that were not considered by the CAPM, these anomalies represent risk premia that have to be considered to explain the returns of stocks. They led to the creation of several multifactor models aiming to better explain the stocks' returns, the goal of these multifactor models is to explain stocks' returns and their covariance matrix as a function of a limited number of risk factors. As stated in Institute of Chartered Financial Analysts. Research Foundation (1994), the multiple factor models (or multifactor models) have far greater explanatory power than the CAPM. Many empirical or econometric studies have proven the multiple factor models superior explanatory performances when including multiple factors to explain returns and multiple factor premiums to explain stocks' expected returns (Hanauer, 2020), (Fama & French, 1993), (Carhart, 1997), (Fama & French, 2018), (Stambaugh & Yuan, 2017). Multiple factor models are based on a simple 4 components linear structure following the form of the APT equation, the components are: a stock's exposures to the factors, the attributed factor returns, the stock excess returns and the idiosyncratic return (or stock specific return).

Multiple factor models are ideal in predicting investment risk and providing investment intuition, they allow to identify intuitive, incisive and important common factors impacting risk and returns. They can be useful in forecasting investment risk and explaining past returns but are not very suited to predict future returns (as they are based on past data and past performance implies no guarantee of future results).

According to Hanauer (2020) the Fama & French six factor model robustly outperforms the competing multifactor models in explaining stock returns. This model is the latest upgraded version of the classical Fama & French three factor model (Fama & French, 1993) that also considers the momentum factor from the Carhart four factor model. The Fama & French six factor model from 2018 put the emphasis on five anomalies that are not considered under the CAPM. These five anomalies along with the CAPM beta form the six factors of this model, namely: the CAPM market risk premium (that had already been discussed before), the value factor, the size factor, the momentum factor, the profitability factor and the investment factor.

The value factor is composed of a long position on the cheapest stocks and a short position on the most expensive stocks (according to their Price to Book ratio). This factor is also commonly called the High minus Low factor (HML) because it is short the returns of the low price to book ratio stocks and long the returns of the high price to book ratio stocks.

The size factor is composed of a long position on the return of the smallest stocks and a short position on the return of the largest stocks (according to their market capitalization). This factor is also commonly called the Small minus Big factor (SMB) because it is short the returns of the big market capitalization stocks and long the returns of the small market capitalization.

The Momentum factor is composed of a long position on the past best performing stocks and a short position on the past worst performing stocks (according to their rate of return). This factor is also commonly called the Up minus Down factor (UMD) because it is short the returns of the stocks that are in a downward trend and long the returns of the stocks that are in an upward trend.

The profitability factor is composed of a long position on the stocks with a high operating profitability[13] and a short position on the stocks with a low or negative operating profitability. This factor is also commonly called the Robust minus Weak factor (RMW) because it is short the returns of the stock that are considered as having a weak operating profitability and long the returns that are considered as having a robust operating profitability.

The investment factor is composed of a long position on stocks requiring little on-going capital investment to maintain and grow their businesses and a short position on stocks requiring large on-going capital investment to do so (according to their asset growth). This factor is also commonly called the Conservative minus Aggressive factor (CMA) because it is short the returns of the aggressive stocks in terms of investment and long the returns of the conservative stocks in terms of investment.

[13] The operating profitability refers to the Earnings Before Interest and Taxes of a company (EBIT).

The Fama & French six factor model can be written as:

$$ER_i = R_f + \beta_{CAPM,i} * (R_m - R_f) + \beta_{HML,i} * HML + \beta_{SMB,i} * SMB + \beta_{UMD,i} * UMD + \beta_{RMW,i} * RMW + \beta_{CMA,i} * CMA + \varepsilon_i$$

Where:

- ER_i is the expected return for stock i
- R_f is the risk-free rate
- $\beta_{CAPM,i}$ is the CAPM beta of stock i
- R_m is the return of the market portfolio
- $\beta_{HML,i}$ is the beta of stock i regarding the value factor
- HML is the value factor
- $\beta_{SMB,i}$ is the beta of stock i regarding the size factor
- SMB is the size factor
- $\beta_{UMD,i}$ is the beta of stock i regarding the momentum factor
- UMD is the momentum factor
- $\beta_{RMW,i}$ is the beta of stock i regarding the profitability factor
- RMW is the profitability factor
- $\beta_{CMA,i}$ is the beta of stock i regarding the investment factor
- CMA is the investment factor
- ε_i is the error term of the equation for stock i

One other well-known multifactor model using other factors is the 2017 four factor model from Stambaugh & Yuan, this model uses the two classical factors of the CAPM risk premium as well as the size factor and adds two new factors that are the management factor and the performance factor.

The management mispricing factor (also referred to as MGMT) is linked to composite scores computed as the average percentile of the stock in comparison with the other stocks from the data set regarding the following stock related metrics: asset growth, composite equity issues, investment-to-assets, net stock issues, net operating assets and operating accruals. This management factor is then composed of a long position on stocks having a low composite score.

The performance mispricing factor (also referred to as PERF) is linked to composite scores computed as the average percentile of the stock in comparison with the other stocks from the data set regarding the following stock related metrics: gross profitability, six-month momentum and return on assets. This performance factor is then composed of a long position on stocks having a low composite score.

The Stambaugh & Yuan four factor model can be written as:

$$ER_i = R_f + \beta_{CAPM,i} * (R_m - R_f) + \beta_{SMB,i} * SMB + \beta_{MGMT,i} * MGMT + \beta_{PERF,i} * PERF + \varepsilon_i$$

Where:

- ER_i is the expected return for stock i
- R_f is the risk-free rate
- $\beta_{CAPM,i}$ is the CAPM beta of stock i
- R_m is the return of the market portfolio
- $\beta_{SMB,i}$ is the beta of stock i regarding the size factor
- SMB is the size factor
- $\beta_{MGMT,i}$ is the beta of stock i regarding the management mispricing factor
- MGMT is the management factor
- $\beta_{PERF,i}$ is the beta of stock I regarding the performance mispricing factor

- PERF is the performance factor
- ε_i is the error term of the equation for stock i

Finally, (Hyde, 2018) demonstrated that an accounting based fundamental analysis of stocks historical information can help to eliminate firms with poor future prospects from a portfolio composed of high book to market ratio stocks, and so help to understand the performance of these stocks. The resulting fundamental factors have been used to determine the financial strength of a company with the Piotroski F-score. This F-score is a score comprised between zero and nine and is the result of the addition of the score of nine binary test on a company financials. These nine tests can be classified into three groups of criteria that will be tested, these three criteria are first the profitability, then the leverage, liquidity and source of funds and finally the operating efficiency. We will now present the nine binary tests below (the result of the test is one if the condition is met and zero otherwise).

Tests for the profitability criteria include:
- A positive net income
- A positive return on asset in the current year
- A positive operating cash flow in the current year
- Cash flow from operation being greater than the net income

Tests for the leverage, liquidity and source of funds criteria include:
- A negative difference between current year and prior year long-term debt
- A positive difference between current year and prior year current ratio
- No issuance of new shares during the prior year

Tests for the operating efficiency criteria include:
- A positive difference between current year and prior year gross margin
- A positive difference between current year and prior year asset turnover ratio

2.8 Hypotheses buildup

After this literature review part, it now seems clear that some hypotheses can already be drawn concerning the behavior that the food and drinks industry stocks should have regarding some variables as they are part of the broader defensive stocks category.

The first hypothesis formed following the literature review state that due to their defensive characteristics the food and drinks industry stocks should be less correlated to the market and hence should exert a smaller CAPM beta than the average stocks. The returns of these stocks should be weakly correlated or even negatively corelated to the CAPM risk premium. This hypothesis is supported by the conclusions from Maarten VET et al (2021) proving that overall, these firms were less affected by the covid-19 crisis. This hypothesis is also supported by Tariq Bhutta & Hasan (2013) that provide evidence that profitability of stocks from the food industry is more shaped by firm specific variables and not by macroeconomic factors.

The second hypothesis formed following the literature review state that the market size of the food industry stocks should be a statistically significant factor in explaining these stock returns as Tariq Bhutta & Hasan (2013) showed that the profitability of firms in the food sector is shaped by firm specific factor and more particularly by the size factor. Ole-Meiludie et al (2014) also proved that the size of a defensive company can impact is beta and that smaller defensive company tends to exert smaller beta.

As this literature review comes to an end, it highlights the fact that although several methods have been developed to try to explain past stock returns, they are generally based on the United States financial markets (Hanauer, 2020) and are rarely focusing on a single sector of stocks but rather on a financial market as a whole. Furthermore, there has been a lot of scientific papers studying the performance of investing in defensive stocks during times of bad economic conditions but none trying to identify the factors explaining the returns of these stocks during these particular periods. The goal of this thesis is to identify these factors within the scope of the European food and drink industry during the covid-19 crisis, so that both the management of the companies from the food and drinks sector can better understand what could help their firm to keep its value and investors to identify which of these companies might become the best performing ones in times of market crisis.

The following sections will try to determine the factors explaining food and drinks industry stock returns during the covid-19 pandemic crisis starting from the factors already present in the scientific literature.

3. Data and methodology

This section will be split in two main parts, the first part will discuss how the stocks and the potential factors for this thesis have been chosen as well as how the data for the analysis has been retrieved. The main part will discuss which methods will be used to determine the factors explaining the returns of the European food and drinks industry stocks, how these methods are implemented, what are their limitations and why they have been retained.

3.1 Data

3.1.1 Time scope and periodicity of stock returns

To determine the time period for this thesis, the level of the Eurostoxx 600[14] index was used as a reference to assess the impact of the covid-19 crisis on the European stock market. The chosen start date for this thesis time period is the 19th of February 2020 because this day represents the highest level of the Eurostoxx 600 before the start of the index decline following a series of bad news and increases in the covid-19 cases around European countries. This day can be considered as the start of the European financial markets decline. The chosen end date for this thesis time period is the 6th of April 2021 because this is on this day than the Eurostoxx 600 reached and exceeded its previous highest level for the first time. This day can be considered as the recovery of the European financial markets and the start of a new normal era post covid. This time scope should be complete for the thesis as it contains a both a downward trend and an upward trend of financial markets, allowing to observe the potential resilience of food and drinks industry stocks during the downward trend and their potential underperformance during the upward trend.

The daily periodicity of stock returns was retained given the short time scope of the thesis in order to gather a maximum of data and try to ensure unbiased and statistically significant results for our analysis. This daily periodicity allows to have a total of 287 daily returns.

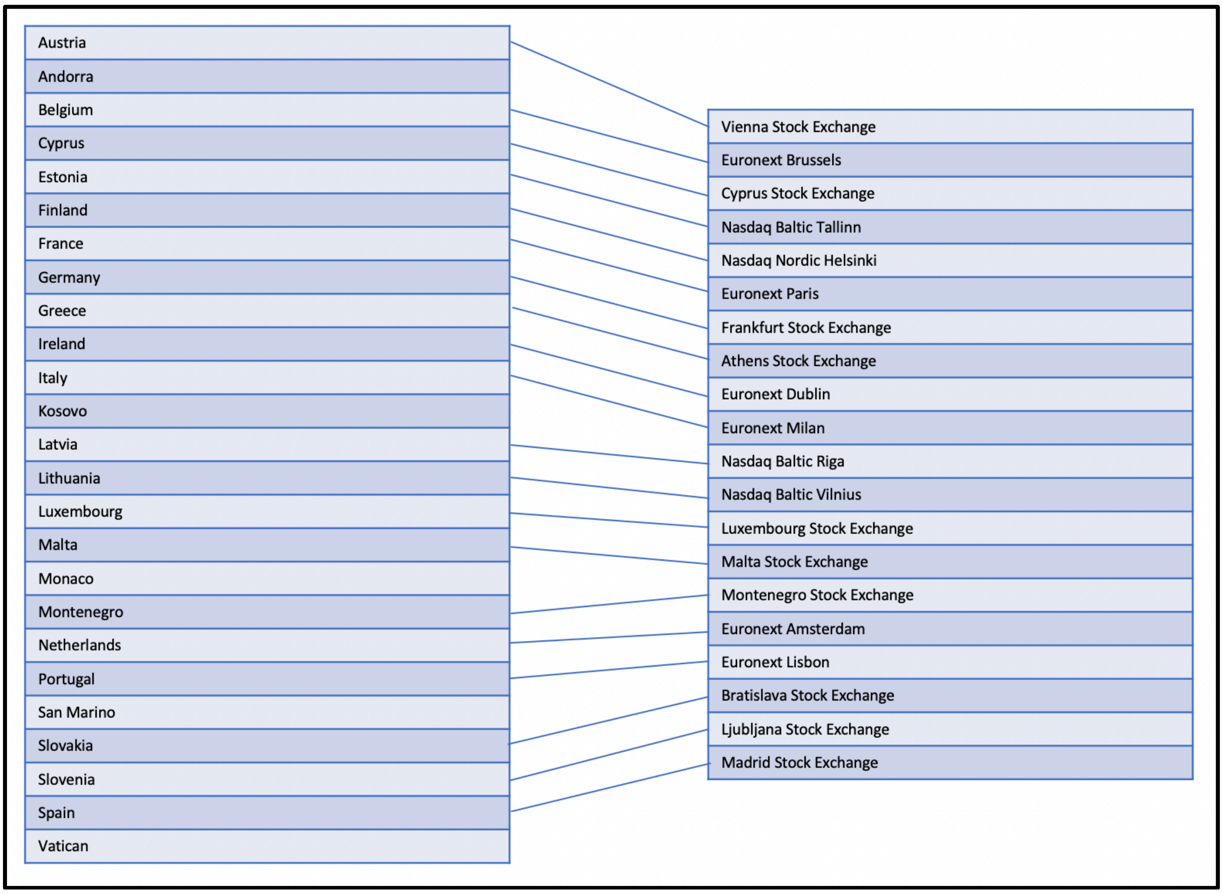
3.1.2 Stock selection process

To try to capture the effect that the covid-19 crisis had on the whole European market, without having to deal with exchange rates of countries being geographically in Europe but not using euro as their currency, a list of the countries using the Euro as their national currency was retained. Then this list of the countries using euro as their currency was reduced to keep only the countries among the list having a national stock exchange (for countries having several national stock exchanges only the main one was kept).

Furthermore, the stocks concerning the food and drinks industry were retrieved from these stock exchanges using the stock exchange sectors related to food and drinks (and eliminating stocks that did not concern the industry when the sectorial groups contained other industries within it). Finally, the stocks for which the relevant data was not available were suppressed from the list. At the end, a final list of 87 stocks were retrieved from the 135 potential European food and drinks industry stocks selected for the thesis.

[14] The Eurostoxx 600 is an index composed of the 600 largest capitalization stocks traded on the major stock exchange of 18 European countries, namely: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxemburg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom.

Figure 2: National stock exchanges retained from the euro countries



3.1.3 Variables selection process

As the goal of this thesis is to try to find the factors explaining the performance of the listed food and drinks industry stocks, a large set of variables need to be defined and tested in order to explain a sufficient part of the stock return variances. To form this variables data set, different stocks, firms and market related pieces of information composing factors from literature review models are retained. From the Fama & French six factor model, the following data are retained: the market portfolio returns (given by the Eurostoxx 600 index), the risk-free rate (given by the 1-year euro area yield curve for AAA government bonds), each stock price at each date, each firm number of shares outstanding, each firm common stockholder equity, each firm preferred equity, each firm EBIT, each firm net income, each firm six-month momentum, each firm asset value and debts value. Then from the Stambaugh & Yuan (2017) and Hyde (2018) researches the following firm related additional data are retained: each firm net income, each firm debt value, each firm proportion of shares issued during the period, each firm sales value. Financial data related to some factors have been intentionally left to avoid too strong correlation between the potential factors and due to a lack of information available concerning these data for some stocks.

Macroeconomic factors were not retained as Tariq Bhutta & Hasan (2013) showed in their study that the profitability of the food sector is determined by factors that are firm specific rather than macroeconomic factors. Moreover, as the time period for this thesis is relatively short and the macroeconomic impact of the covid-19 crisis was broadly the same for all the European countries, the potential macroeconomic factors are neglected in this thesis.

The final variables to be used in the principal component analysis are the CAPM market risk premium, and for each stock the following stock related variables: market capitalization, price to book ratio, six-month momentum, EBIT, asset growth, net income, return on assets, debt growth, proportion of share issuance, gross margin, assets turnover growth and leverage.

The data to form all these variables is extracted from the Bloomberg Terminal[15] software, the Yahoo finance website database, the European central bank website as well as the national stock exchange websites, all the stock related data (apart from the returns and the proportion of shares issuance) will be standardized before being used for the principal component analysis.

[15] The Bloomberg Terminal software is a software from the financial data company Bloomberg L.P.

3.2 Methodology

The goal of this thesis is to try to identify the factors explaining the food and drinks industry listed stocks returns during the covid-19 crisis. Now that the stocks, the variables and the time period have been defined, this second section will discuss the methodology used to determine these factors and test their explanatory power regarding this thesis stock returns. First, the data sample adequacy for factor analysis will be tested with the Kaiser-Meyer-Olkin criterion. Secondly, a principal component analysis in its varimax rotation form will be used to determine the factors explaining the most variance in the stock returns. Finally, a Fama Macbeth regression will be done on the retained rotated principal components to test if they exhibit a statistically significant risk premium.

3.2.1 Kaiser-Meyer-Olkin criterion

The approach of Hargreaves et al (2015) will be followed by realizing a Kaiser-Meyer-Olkin criterion test to ensure that the variables can be factorized efficiently. The Kaiser-Meyer-Olkin criterion (or KMO) is a statistical sampling adequacy test that measures the proportion of variance among the variables that might be common variance to determine how suited the data is for factor analysis. This test returns a value between 0 and 1, the closer to one the result is, the higher the proportion of variance is common variance (the lower the proportion of variance related to partial correlation) and the more efficiently the original variables can be factorized. Value of the KMO above 0.5 are commonly accepted for indicating the sample adequacy for factor analysis while KMO below 0.5 are considered as unacceptable meaning that the sample is inadequate for factor analysis. The KMO criterion formula can be written as:

$$\mathrm{KMO} = \frac{\sum_{i=1}^{n}\sum_{j=1,j\neq 1}^{n} r_{i,j}^{2}}{\sum_{i=1}^{n}\sum_{j=1,j\neq 1}^{n} r_{i,j}^{2} + \sum_{i=1}^{n}\sum_{j=1,j\neq 1}^{n} p_{i,j}^{2}}$$

Where:

- $r_{i,j}$ is the correlation between the variable i and the variable j
- $p_{i,j}$ is the partial correlation between the variable I and the variable j

One limitation of the KMO is its inability to process with a singular correlation matrix (correlation matrix whose determinant is equal to 0), these kind of correlation matrixes can be encountered with variables that are very highly or even perfectly correlated. In order to avoid this type of matrix, a correlation matrix heatmap will be realized and variables that are too correlated will be removed.

3.2.2 Principal component analysis (PCA)

In order to reduce the dimensionality of our potential datasets and try to reduce pair-wise correlation between the variables, an inspiration is taken from the approaches of Hargreaves et al (2015), Malkov (2019), Jollife & Cadima (2016) and Pukthuanthong et al (2018), by applying a principal component analysis on the factors data. This method will provide a smaller number of principal components that are linear combinations of the potential factors while still explaining a sufficient amount of the total variance.

Principal Component Analysis (PCA) is a commonly employed method for explanatory data analysis and predictive models. The method consists in computing the principal components (from which it takes its name) of a collection of points in a real coordinate space. These principal components can be defined as a sequence of X unit vectors (vector with a length of 1 in a normed vector space) where each vector x is the direction of a line that minimizes the average squared distance from this line to the data points while being orthogonal to the precedent vectors. These orthogonal lines form an orthonormal basis in which each one of the different data dimensions are linearly uncorrelated. These lines are the principal components of the dataset.

These principal components can then be used to change the basis of the data and in this case to reduce the dimensionality of the data. The goal of this dimensionality reduction is to avoid overfitting the thesis potential new model, which might lead to conclusions that would not generalize to other datasets, by trying to reduce the number of principal components (explanatory variables) while ensuring that a sufficient level of the original dataset variance is preserved. By keeping a small number of principal components p, a p-dimensional plane can be obtained from the high-dimensional original dataset in which the potential data and data clusters will be the most scattered. This high level of data scattering allows to have a better visibility and graphic retranscription for the potential data clusters than with a lower level of scattering that might let the clusters overlay each other. As most of the total variance is contained in the first principal components and each of the following additional principal component contains less and less variance, the first principal components only can be kept while ensuring the sufficient level of variance and the latter principal components that contain only a small proportion of the total variance can be left out without great loss.

One common pitfall concerning PCA is that PCA is scale variant and hence some variables might dominate others because of their bigger values. In order to avoid this pitfall, the data for the factors will be standardized.

A second limitation of the PCA is the fact that there is no optimal number of principal components to keep to ensure that a sufficient level of variance is kept without losing too much information. There are three commonly used techniques to decide how much principal components need to be retained: the visual inspection of the scree plot (Malkov, 2019), the minimum amount of total variance explained (Hargreaves et al., 2015), (Malkov, 2019) and the principal components with eigenvalues greater than one (Hargreaves et al., 2015). All these techniques will be applied in order to decide the number of principal components that will be retained.

The main issue of the PCA is the lack of economic interpretability of the principal components, the principal components are linear combinations of the original potential factors with different loadings for each of them. In order to simplify the principal components interpretability, one can simplify the structure of these components using a rotation technique. This thesis takes inspiration from previous work from, hence a varimax rotation will be applied on the retained principal components.

3.2.3 Varimax rotation

In order to increase the interpretability of the principal components, a varimax rotation will be applied. This varimax rotation will allow to highlight a small number of important variables within the principal components by maximizing the sum of the variances of the squared correlations between the variables and the factors. This second step performs an orthogonal rotation within the principal components subspaces to align them with the coordinates of the most explanatory variables. The method should lead to higher loadings for the few most important variables and lower loadings for the rest of the variables which should help for the economical interpretation of the principal components.

3.2.4 Construction of the risk factors

As the Fama Macbeth regression requires returns associated to the risk factors, the method preconized by Lambert et al (2018) will be followed. The construction of the long-short portfolios will be done using a 3x3 symmetric sort with a preconditioning on the control variable. The long-short portfolio related to the priced variable will be constructed by dividing the stocks in three subgroups according to their positioning regarding the control variable (the breakpoints being the top 30 percentiles and the worst 30 percentiles) and then each of these 3 subgroups will again be divided into three subgroups according to the stocks positioning regarding the priced variable in order to form a total of 9 subgroups. Then these 9 subgroups will be used to form equally weighted portfolio from which average returns will be computed. Finally, the average returns of six out of the nine portfolios will be used to compute the long-short portfolio returns associated to the risk factor.

In this thesis, the long short portfolio related to the first rotated component will be created using the second rotated component as control variable and the first RC as the priced variable and the following portfolios using the first RC as control variable and the risk factor related RC as priced variable.

3.2.5 Fama Macbeth regression

Following the methodology of Ramovic & Åkerman (2021) after the determination of the risk factors (rotated components from the varimax rotated PCA) the stocks betas or exposures regarding the risk factors and the risk factors m-premia will be computed. The Fama Macbeth two step regression method will be used to do so. This cross-sectional regression of returns on risk factors allows to estimate the premium rewarded for one-unit exposure to a particular risk factor by the market. The significant risk premia from the regression will help understand how the principal components describe the portfolio returns.

One main pitfall from the Fama Macbeth regression is the potential Error-In-Variables, this pitfall comes from the fact that the beta estimates from the OLS regressions are used as independent variables in cross-sectional risk premium regressions, this can lead to an accumulation of estimates uncertainty and skewing t-statistics. In order to avoid this phenomenon, the approach of (article 22) will be followed and for each risk factor regression, the stocks will be classed in the subgroups used to construct this risk factor and the stocks will be assigned this recession group mean beta as their beta regarding the risk factor for the second regression determining the risk premia.

The first step of the method is a time-series regression in which each daily stock returns will be regressed on the factors to estimate the factor loadings and can be written in its matrix form as:

$$\underset{\mathrm{D \times 1}}{\mathrm{r_i}} = \underset{\mathrm{D \times (N+1)}}{\mathrm{F}} * \underset{\mathrm{(N+1) \times D}}{\beta_i} + \underset{\mathrm{D \times 1}}{\epsilon_i}$$

Where:

- $\mathrm{r_i}$ are the daily excess returns of stock i
- F are the risk factors
- β_i are the betas of stock i regarding the risk factors
- ϵ_i are the residuals regarding excess returns of stock i
- D is the number of daily periods
- N is the number of factors

The second step of the method is a cross-sectional regression that will be done to estimate the risk premiums and can be written in its matrix form as:

$$\underset{\mathrm{S \times 1}}{\mathrm{r_t}} = \underset{\mathrm{S \times (N+1)}}{\hat{\beta}} * \underset{\mathrm{(N+1) \times 1}}{\lambda_t}$$

Where:

- $\mathrm{r_t}$ are the excess returns for each stock at time t
- $\hat{\beta}$ are the stock betas regarding the factors

- λ_t are the risk premia for each stock at time t
- S is the number of stocks

After these two regressions, the factor risk premia will be computed as the time average of each individual daily risk premia and tested with a t-statistic to assess their statistical significance.

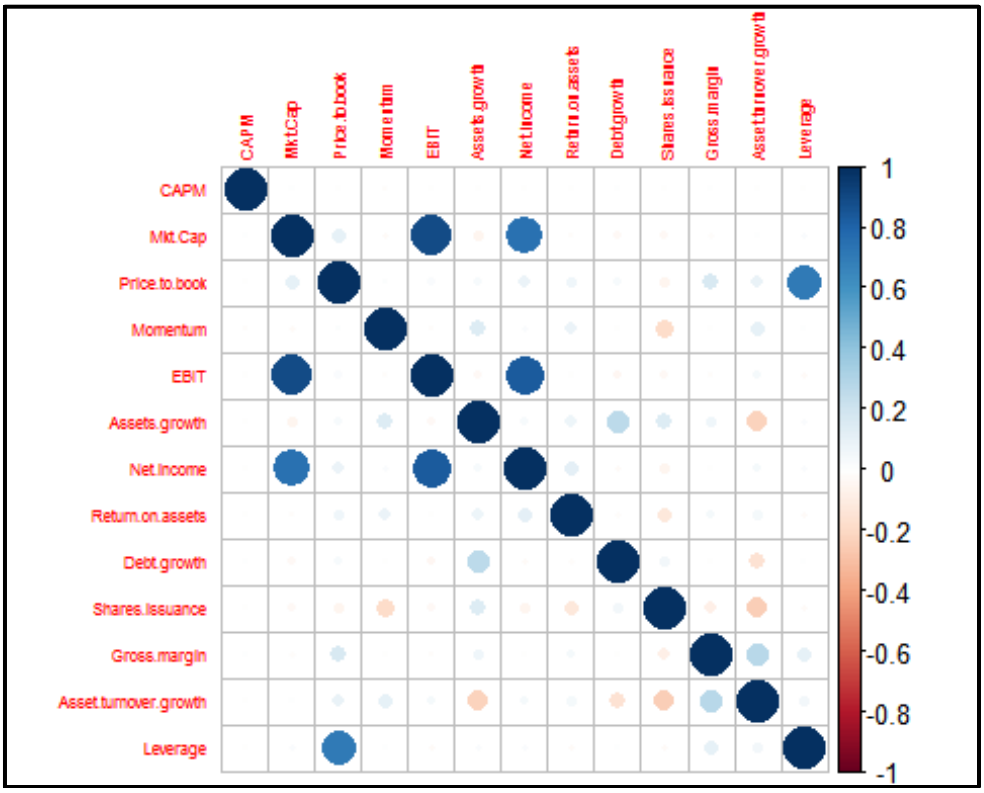
During this section the data, the different steps that will be used during this thesis to identify relevant factor to explain the food and drinks industry stocks have been presented. The next section will present the results from the different steps, the potential factors to explaining the stock returns and the different explanations or conclusions that can be drawn from it.

4. RESULTS

In this section, the results from the statistical test and methods to identify the factors explaining the food and drinks industry stocks returns will be discussed. First, in order to ensure the proper functioning of the KMO criterion and to avoid a singular correlation matrix, a look was given at the correlation matrix to ensure that there was no perfectly or too correlated factors. Secondly, the results from the principal component analysis were analyzed to select the number of principal components needed to retain in order to simplify the structure of the data set without losing too much explanation power. Thirdly, the retained principal components were rotated using a varimax criterion to simplify their structure and their interpretation, the rotated principal components were used to create risk factor long-short portfolios. Fourthly, the premia related to exposure to the risk factors and their significance were assessed using the Fama-Macbeth regression.

Figure 3 shows a heat map of the correlation matrix of the variables from the 19th of February 2020 to the 6th of April 2021, dark blue dots along the diagonal line shows perfectly positively correlated variables, white cases show uncorrelated variables and red dots shows negatively correlated variables. From this correlation matrix heat map, we can observe that there are four strong pairwise correlation (Market Capitalization and EBIT, Market Capitalization and Net Income, Price to Book ratio and Leverage, EBIT and Net Income). Although Market Capitalization and EBIT exhibit a particularly strong pairwise correlation, these two variables are very different in their economic interpretation and for these reasons were both kept. The three others strongly correlated pairs were judged sufficiently different from one another to be considered as standalone variables in the rest of this thesis process.

Figure 3: Correlation matrix heat map of the variables



Source: R code from this thesis

4.1 KMO

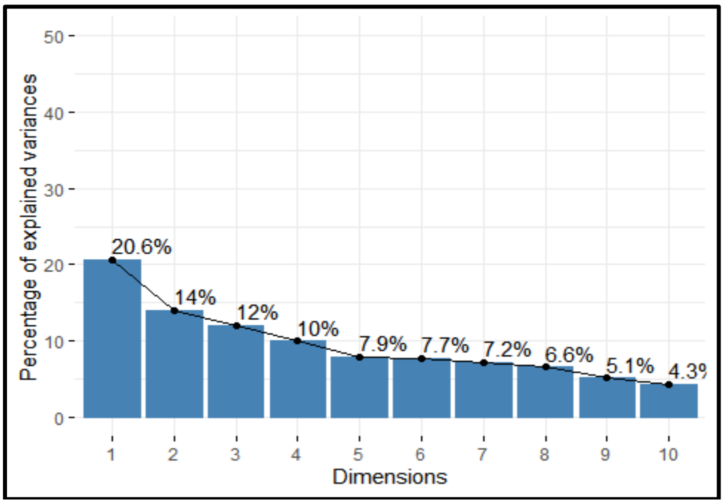
The first step of this thesis was the to apply a KMO test on the dataset to assess the statistical sampling adequacy of it for factor analysis by comparing the proportion of common variance to the proportion of partial variance in the dataset. The result from the KMO was 0.615, as this result is lower than 0.7 and higher than 0.6, the dataset can be qualified as mediocre. The mediocre status and the result above 0.5 ensure that the dataset is suited for factor analysis, hence a principal component analysis can be applied.

4.2 PCA

The second step of this thesis was to apply a principal component analysis to the potential variables dataset in order to reduce its dimensionality. This process will construct principal components orthogonal to each other's and that are linear combinations of the original variables. As the first principal components contains most of the total variance and each additional principal components contains less and less variance, the optimal number of principal components to retain in order to reduce the dimensionality need to be determined. There are several techniques in order to determine this optimal number of PCs and the three most commonly used will be applied.

The first common technique used to determine the number of principal components that needs to be retained relate to the visualization of the PCA scree plot, figure 4 shows this scree plot. A slight kink can be observed after the 6th principal component. According to this technique the 7th and beyond components can be considered as having a lower contribution to the total variance and can be left without losing too much explanatory power.

Figure 4: Scree plot of the principal components



Source: R code from this thesis

The second common technique used to determine the optimal number of PCs relate to the minimum amount of total variance to be explained, one common threshold for this minimum is 70% of cumulative total variance. The proportion of variance explained by each PC can be observed in figure 5. According to this technique the 70% threshold is reached and exceeded by the 6th principal component, hence this second technique confirms that retaining only the 6 first PCs will be sufficient to explain 70% of the dataset variance.

Figure 5: Importance of the components from the Principal Components Analysis

	Eigenvalue	Proportion of variance	Cumulative proportion
PC1	2.6774590	0.2059584	0.2059584
PC2	1.8237341	0.1402872	0.3462456
PC3	1.5547787	0.1195984	0.4658440
PC4	1.2960859	0.09969891	0.56554290
PC5	1.0248331	0.07883331	0.64437621
PC6	0.9997343	0.07690264	0.72127885
PC7	0.9407286	0.07236374	0.79364259
PC8	0.8536618	0.06566629	0.85930888
PC9	0.6670517	0.05131167	0.91062055
PC10	0.5536618	0.04258937	0.95320992
PC11	0.2877633	0.02213564	0.97534556
PC12	0.2392925	0.01840712	0.99375268
PC13	0.0812152	0.006247323	1.000000000

Source: R code from this thesis

The third common technique used relate to the eigenvalues of the principal components, following this technique one must retain all principal components exhibiting eigenvalues equal or greater than one (the bigger the eigenvalue and the most variance is explained by the PC). Figure 5 shows the eigenvalue for each principal component and according to the technique the 5 first PCs must be retained, although the 6th is very close to the threshold eigenvalue of 1. The result from this technique is overall in accordance with the two previous numbers of PCs to retain, for the rest of this thesis the 6 first PCs will be retained.

Figure 6 shows the loadings of the original variables within each of the PCs, we can see that some variables are more represented in certain PCs and less in others but there is still a lot of variables that are represented by small but significant loadings in each PCs making them hard to interpret economically.

Figure 6: Principal components variables loadings

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13
CAPM Market Risk Premium	0.00056692	0.00210909	0.00309360	0.02478160	0.16850970	0.98158281	0.07410373	0.04315777	0.00951189	0.00507389	0.00000192	0.00089442	0.00047149
Market Capitalization	-0.56711482	0.07638281	0.04291059	0.05338018	0.01724350	-0.00692088	0.05153826	-0.01523999	-0.01880522	0.07627710	-0.17843847	-0.59051024	-0.52716936
Price to Book ratio	-0.10354705	-0.59666311	0.29075939	0.13152536	-0.14657521	0.02509817	-0.03486216	-0.02002372	0.03911563	0.01797712	-0.68005495	0.19849762	0.06301918
6-month Momentum	-0.00534204	-0.11057376	-0.11300944	-0.55226468	-0.32389373	0.01249552	0.47636359	0.40252026	0.22218622	0.35576557	-0.00268262	-0.00499900	-0.00116000
EBIT	-0.58522365	0.11205578	0.00476510	0.01235045	0.04867042	-0.01317775	0.05361534	0.00368722	0.00498115	0.01338915	0.01877806	-0.12472260	0.78945453
Assets growth	0.03272313	0.04088195	0.46689144	-0.48748158	0.19075456	-0.02929530	0.00846090	0.28308724	-0.28294287	-0.57709464	-0.04507493	-0.09488932	0.00677088
Net Income	-0.55606443	0.05750771	0.03627421	-0.08465481	0.00262674	0.00461650	-0.06012242	0.02908511	0.02369141	-0.06445999	0.21889135	0.72732709	-0.30476156
Return on Assets	-0.04379939	-0.10453052	-0.08053205	-0.43007807	-0.22623389	0.11190860	-0.81583179	-0.05117681	0.17603575	0.10273384	0.05389388	-0.13445064	0.03566790
Debt growth	0.04524001	0.05283466	0.41735009	-0.30672897	0.22564375	-0.02153498	0.19354846	-0.68273547	0.38065325	0.15569553	0.05279230	0.00118200	-0.00202133
Shares Issuance	0.06380206	0.22429799	0.39861722	0.28788035	0.21254074	-0.06089041	-0.17978243	0.51354650	0.58367889	0.13499807	0.00270316	0.00029799	-0.00174820
Gross Margin	-0.01492348	-0.32939935	-0.11672343	-0.14445863	0.73617830	-0.12027859	-0.09944712	0.14494795	-0.26264142	0.44432062	0.05210180	0.01701315	-0.00708980
Assets Turnover growth	-0.05960789	-0.31943082	-0.48422259	-0.05217115	0.28264264	-0.05409037	0.09233691	-0.00418894	0.53122316	-0.52748203	-0.00123626	-0.06927432	-0.02500835
Leverage	-0.05525578	-0.57777602	0.30635394	0.20921028	-0.19244974	0.02281254	0.05808477	0.03129645	-0.01647068	-0.03483157	0.66855440	-0.18745483	-0.00074165

Source: R code from this thesis

4.3 Varimax rotation and interpretation of the rotated components

The third step of this thesis was to apply a varimax rotation to the 6 retained principal components in order to simplify their structure and increase their interpretability. The new linear combinations of the original variables issued from this step are called rotated components or RCs. Figure 7 shows the loadings for these newly built RCs, the variables that previously exhibited high loadings within a PC now exhibit even higher loadings within the RC and variables that previously had low loadings have now reduced loadings. After the simplification of the components' structures, these rotated components were interpreted according to the variables exhibiting the largest loadings inside them (in absolute values) as these variables are those which contributes the more to the component.

Figure 7: Rotated components variables loadings

	RC1	RC2	RC3	RC4	RC5	RC6
CAPM Market Risk Premium	0.00	0.00	0.00	0.01	0.00	1.00
Market Capitalization	0.93	0.05	-0.04	-0.04	-0.02	0.00
Price to Book ratio	0.06	0.92	0.03	0.05	0.10	0.00
6-month Momentum	-0.03	-0.01	0.12	0.72	-0.03	-0.07
EBIT	0.97	-0.03	-0.04	-0.01	0.01	0
Assets growth	0.00	0.01	0.82	0.14	-0.01	-0.01
Net Income	0.91	0.03	0.03	0.10	0.01	0.00
Return on Assets	0.04	0.02	0.09	0.57	-0.01	0.05
Debt growth	-0.03	0.01	0.67	-0.02	0.00	0.01
Shares Issuance	-0.03	-0.03	0.31	-0.60	-0.21	-0.01
Gross Margin	-0.01	0.09	0.18	-0.06	0.88	0.00
Assets Turnover growth	0.02	0.03	-0.38	0.22	0.67	-0.01
Leverage	-0.01	0.93	-0.01	-0.02	0.02	0.00

Source: R code from this thesis

The factors with the largest loadings within first rotated component (RC1) are the market capitalization, the EBIT and the Net income, the combination of these three factors within one RC is not surprising as the correlation matrix heatmap (figure 3) already shows the strong correlation between these 3 factors. These 3 factors are linked to the size of the company, as the bigger the company, the bigger its market capitalization and the bigger its EBIT and net Income all other things being equal. According to the loadings of these factors, large companies with large profits would have a high score regarding this component. As such this component is labelled *"Span"* to refer to the span or size of the company without using the word size generally associated to the market capitalization of the company only.

The factors with the largest loadings within the second rotated component (RC2) are Price to Book and Leverage ratios. Both these ratios are impacted by the company level of equity as the leverage ratio is computed in its debt-to-equity ratio form in this thesis. As price to book ratio is a measure of the valuation that the market grant to a company and reflect confidence or not in the business, or exposition to the business risk, leverage can be seen as a measure of financing risk that can be considered or not as a part of the business risk. According to these factor loadings, companies that are valued more than their book equity and with a positive leverage would have a high score regarding this component. The strong valuation of a company despite this company exhibiting a significant level of leverage reminds of growth stocks, these stocks for which investors have high expectations in the future despite a lack of current results or fragile financial structure. To reflect this view of confidence and expectations from the investors, this component is labelled as "*Investors faith*".

The factors with the largest loadings within the third rotated component (RC3) are Assets growth, Debt growth and Assets turnover growth. Although the first two factors have positive loadings, the Assets Turnover growth has a negative loading and hence negatively impact the component. As assets turnover is a measure of the relative to the assets, this measure is negatively impacted by growing assets and hence can exert a negative growth in case of a company assets growing faster than its revenues. These two first factors seem to be positively affected by a company growth in terms of assets (the long-term debt growth can be interpreted as a growth financed by debt) and the third factor seems to be negatively impacted by a growth of the assets company that is not followed by a proportional increase of the company revenues. According to the factor loadings companies that are expanding their balance sheet or grow their assets have a high score regarding this component and hence this component is labelled as "*Balance Sheet expansion*".

The factors with the largest loadings within the fourth rotated component (RC4) are 6-month momentum, Return on Assets and Shares issuance. The two first factors exhibit positive loadings while the third factor Shares issuance exhibits a negative loading and is hence negatively correlated with the component. The issue of new shares can be seen as a company need for cash not financed by debt and therefore an inability to generate or pledge the cash needed by the current results. The two first measures reflect the company profitability for the investor. This component is labelled "Investment *profitability*" to reflect the loadings according to which a company generating large revenue relative to its assets and hence excess cash would have a high score regarding this component.

The factors with the largest loadings within the fifth rotated component (RC5) are Gross Margin and Assets Turnover growth. These two ratios are linked to the generation of revenues compared to the gross costs for the Gross margin and to the Assets for the turnover growth. According to these factor loadings a company able to generate strong revenue proportionally to its assets and gross costs would have a high score regarding this component. To reflect this observation this component is labelled "*Sales efficiency*".

The factor with the largest loading within the sixth rotated component (RC6) is the CAPM risk premium. As this factor is the only one with a significant loading within the RC, this component is labelled "*CAPM risk premium*". According to this factor loading, companies exhibiting strong correlation with the "Market Risk" (Eurostoxx 600 minus 1-year euro area yield curve) would have a high score regarding component. This component is particularly interesting as a highly positive premium linked to this component would be a sign of strong correlation between the European food and drinks industry stocks and the market as a whole, in contradiction to the general belief in the literature for these stocks that are considered as defensive and hence less correlated to the broad market moves.

4.4 Fama-Macbeth regression

The fourth step of this thesis was the application of a Fama-Macbeth regression on the rotated components long short portfolios (considered here as the risk factors). This regression is useful to determine each stock exposure to the risk factors and how much of the stock return is driven by this risk factor trough the premium identified by the regression.

The first observation that can be done through to the Multiple R-squared from the regression is that the explanatory power of the model is relatively low (0.303). This observation can be a consequence of the relatively short time period of the thesis (283 days from the 19th of February 2020 to the 6th of April 2021) and gives insight regarding the explanatory power of the risk factors.

The second observation is that 3 risk factors exhibit a positive correlation with the stock returns while the 3 others exhibit a negative correlation. The "Span", the "Investor faith" and the "Balance sheet expansion" factors exhibit negative premia and have hence been negatively correlated with the stock returns, while the "Investment profitability", the "Sales efficiency" and the "CAPM Market Risk Premium" factors exhibited a positive premium and hence were positively correlated to the stock returns. Although the risk factors premia give us indication on whether the factors are positively or negatively correlated with the stocks returns, these premia cannot be interpreted with certainty as they are statistically non-significant.

In this section the statistical results of the methodology used by this thesis to identify relevant risk factors to explain the European food and drinks industry stock returns were presented. In the following section, these results will be discussed more in depth and interpreted, the conclusions regarding these results will be presented and confronted to the original hypotheses from the literature review.

Figure 8: Fama-Macbeth regression estimates for daily data

	Estimate	Standard Error	z-value	Pr(>|z|)
Intercept	-3.5754547	3.6969363	-0.9671	0.3335
Span	-0.0027956	0.0043722	-0.6394	0.5226
Investors faith	-0.0059931	0.0166389	-0.3602	0.7187
Balance sheet expansion	-0.0106805	0.0069163	-1.5442	0.1225
Investment profitability	0.0458093	0.0376023	1.2183	0.2231
Sales efficiency	0.0049869	0.0081338	0.6131	0.5398
CAPM market risk premium	0.3933906	0.3126411	1.2583	0.2083

Total sum of squares: 21672

Residual sum of squares: 15105

Multiple R-squared: 0.303

Source: R code from this thesis

5. Discussion

In this section, first the results from this thesis method to try to identify risk factors explaining the European food and drinks industry stock returns will be interpreted and discussed more in depth. Secondly, conclusions that can be drawn from these results and observations will be presented. Finally, the results from this thesis methodology will be confronted to the hypotheses stated in the literature review to assess whether or not they still hold, have been confirmed or infirmed.

The goal of this thesis was to try to identify relevant risk factors that can explain the returns of the stocks related to the European food and drinks industry during the covid-19 crisis. Following the selection of the potential variables according to the literature review, a principal component analysis was processed on the data set in order to reduce its dimension. 6 components were retained from the PCA and then rotated in order to increase their economical interpretability. The different original variables exhibiting large weights within the rotated components and the economic interpretation of these components was done in the results section. The 6 rotated components have been labelled as "Span", "Investor faith", "Balance sheet expansion", Profitability", "Sales efficiency" and "CAPM Market risk premium".

The results of the Fama-Macbeth regression show that the risk factors constructed from the rotated components and composed of the classical variables coming from the most known multiple factor models fail to explain significantly the returns of the European food and drinks industry stocks. According to the regression, none of the risk factor exhibit a statistically significant premium to explain stock returns and in addition to that the z-score being close to 0 also highlights the lows significance of the risk factors in predicting the stocks returns in this study. Only 3 risk factors exhibit z-score with absolute values greater than one, namely the "Balance sheet expansion", the "Investment profitability" and the "CAPM market risk premium" factors.

The first observation concerns the Span risk factor, this factor exhibits a negative premium in the regression but this premium is not statistically significant. Nevertheless, this negative premium related to the span or size of the company might confirm the findings from (Tariq Bhutta & Hasan, 2013) stating that small defensive companies (according to their market capitalization) exert even smaller beta. This smaller beta for company with smaller market capitalization might have helped them achieve better return and hence reinforcing the negative premium associated to the Span risk factor although as the premium is not significant no real conclusions can be drawn from this observation.

The second observation concerns the "Investor faith" risk factor, this factor exhibits a non-significative negative premium. Hence this risk factor seems to be negatively correlated with the returns of this thesis stocks. The stocks for which investors had the highest expectations might have underperformed in comparison with the rest of the stocks sample.

The third observation concerns the "Balance sheet expansion" risk factor, this factor exhibits a negative premium. As the variables with the largest loadings within this component are linked to the growth of a company assets, the conclusion that can be drawn from this observation is that the expansion or growth of the company assets during the covid-19 period has had a negative effect on the company return. As the covid-19 crisis has had various effects on the different company forming this thesis sample due to the lockdowns restrictions impacting positively some types of business and negatively others, one hypothesis from this thesis to justify this effect lies in the fact that some of the companies that were badly impacted might have been financially at risk because of big investments or assets growth project that they have undertaken and that they might not be able to reimburse as efficiently and quickly as expected due to the covid-19 crisis linked perturbations in their businesses. Even company that have been positively affected by the covid-19 crisis in terms of volume of goods sold might have had to undertake investments or expansion projects not in the most efficient way in order to satisfy the strong increase in the demand for this product. This thesis assumption regarding the negative impact of the "Balance sheet expansion" factor on the returns of the European food and drinks industry stocks is that this phenomenon might be linked to investments or expansion projects that were not taken in the best financial conditions and might have generated some underperformance.

The fourth observation concerns the "Investment profitability" factor. This risk factor exhibits a positive premium, this premium is also relatively large in comparison with the other premia. Although the premium was not statistically significant, this observation seems to go in line with the general belief that investors tend to base at least partially their future expectation concerning a company performance on this company previous performance.

The fifth observation concerns the "Sales efficiency" factor. This risk factor exhibits a positive premium and hence seems to be positively correlated to this thesis stocks returns. This observation might highlight a potential outperformance for companies exhibiting value stocks characteristics of strong margins and assets efficiency (in opposition to growth stocks) but this potential outperformance has to be considered carefully as this risk premium is not statistically significant.

The sixth observation concerns the "CAPM market risk premium" factor, this risk factor exhibits a positive risk premium that is relatively large in comparison with the others risk factors premia. This observation can lead to the conclusion that this factor has impacted positively the return of this thesis stocks during the covid-19 crisis. This effect is in line with the general theory of the CAPM but seems to contrast with the theoretical and empirical assumptions concerning the behavior of the defensive stocks as these stocks are expected to react in a lesser extent to market moves, and the only variable related to these market moves (and more particularly to the CAPM risk premium) seems to be the one with the biggest impact on the stock return in this thesis.

According to the results of the Fama-Macbeth regression, the hypotheses stated at the end of the literature review do not hold true in this thesis.

The first hypothesis stated that due to the defensive characteristics of the food and drinks industry sectors, the stocks should be weakly or even negatively correlated to the CAPM market risk premium, however the results show a positive correlation between the CAPM market risk premium and the returns through the 6th risk factor. This result is in contradiction with the results from (Levy, 1984) that highlight the low correlation between defensive sectors returns and the CAPM market risk premium that has previously even been higher in times of financial distress. The results lead to the reject of this hypothesis in this thesis and can lead to the question of whether or not the behavior of defensive stocks differed during the covid-19 crisis in comparison with previous times of bad financial market conditions.

The second hypothesis stated that the market size of the companies composing the data sample should be a significant factor in the explanation of these stocks returns, unfortunately, there are no signs of statistically significant risk premium assigned to the market size of the company in this thesis results. The only component inside which the market capitalization has a high loading is the Span risk factor that is strongly related to variables dependent of the company size and this risk factor does not exhibit a significant risk premium in the regression. Hence this hypothesis is rejected.

The results of this thesis are not really in line with those of previous financial research and this might be the consequence of the covid-19 financial crisis particular aspects in comparison with previous crisis. The covid-19 pandemic crisis has had a wide variety of impacts on European food and drinks companies in function of their businesses lines as the qualification of these businesses as "essentials" or not altered their ability to operate normally. As such the observation from this thesis are to be carefully considered when comparing to thesis related to different financial crisis. Moreover, the covid-19 financial crisis was short lived as the Eurostoxx600 only took 412 days since the start of its decline to recover its previous highest level and 384 days since its lowest level during the crisis. This short time window strongly restricts the number of observations for the thesis even with daily data. One second element restricting the explanatory power of this thesis is the yearly periodicity of most of the firm related factors, these yearly updated factors tested on a time period of two partial years unfortunately restricts the explanatory power of this thesis.

Further research could try to replicate this method with data reflecting previous and potentially longer financial crisis from which more data might be available. Using different periods might be interesting in order to observe whether or not this thesis factors can better explain the European food and drinks industry stocks returns differed during others financial crisis. Longer time period might also be interesting as this would imply more data and potentially more explanatory power from the regression and potentially more statistically significant premia associated to the risk factors. Reproducing this thesis methodology with other classical defensive sectors might be interesting to observe potential similitudes or differences between the food and drinks industry stocks and the others sectors commonly considered as defensive.

6 Conclusion

Numerous studies have focused on explaining stocks past returns or returns from strategies focusing on particular stocks or sectors but there is no research that tries to explain the returns of defensive stocks (and more particularly the European food and drinks industry stocks) through a set of firms related factors. The singular covid-19 crisis that the world faced in 2020 and 2021 has highlighted the difference in essentiality between various businesses and sectors even among the classical defensive sectors. This particular situation offers an opportunity to try to model through risk factors what are the determinants of the European food and drinks industry stocks returns.

In order to try to explain the performance of the European food and drinks industry stocks, this research retrieved the following list of potential risk factors from the financial literature concerning the defensive equity and the multiple factor models: the CAPM market risk premium, the market capitalization ,the price to book ratio, the 6-month momentum, the EBIT, the assets growth, the net income, the return on assets, the debt growth, the proportion of shares issuance, the gross margin, the assets turnover growth and the leverage. These factors were linearly combined in principal components using a principal component analysis in order to reduce the dimensionality of the data set and then rotated to increase their interpretation. Finally, the thesis stock returns were regressed against the risk factors created from the rotated component in order to try to identify significant risk premia linked to these risk factors.

The statistical results of this thesis fail to explain the European food and drinks industry stocks returns using variables from the classical multiple factor models and gave only slight indications of how the risk factors impact the stock returns as the risk factors exhibit non-statistically significant premia. Although this thesis results regarding the classical defensive assumptions are mitigated and hence do not allow to confirm neither infirm these assumptions. The loadings associated to the thesis risk factors and their interpretations give potential insights on how these risk factors might have impacted the European food and drinks industry during the covid-19 crisis and might impact them during a similar crisis in the future. Further research could focus on observing if the impact of these risk factors on the food and drinks sectors is the same across other periods of financial distress but also if the other defensive factors seem to be impacted in the same way as the food and drinks industry. These potential researches might offer more relatable points of comparisons allowing for deeper interpretation and comprehension on what were the factors impacting the stock returns during the covid-19 crisis.

Appendices

Appendix A: List of stocks retrieved for the thesis

Name:	ISIN code:	Bloomberg ticker:	Country:	Stock exchange:
AGRANA BETEILIGUNGS-AG	AT000AGRANA3	AGR AV	Austria	Vienna Stock Exchange
DO & CO AKTIENGESELLSCHAFT	AT0000818802	DOC AV	Austria	Vienna Stock Exchange
GURKTALER AG ST	AT0000A0Z9G3	GAGS AV	Austria	Vienna Stock Exchange
JOSEF MANNER & COMP. AG	AT0000728209	MAN AV	Austria	Vienna Stock Exchange
OTTAKRINGER GETRÄNKE AG ST	AT0000758008	OTS AV	Austria	Vienna Stock Exchange
AB INBEV	BE0974293251	ABI BB	Belgium	Euronext Brussels
CO.BR.HA	BE0003519270	COBH BB	Belgium	Euronext Brussels
COLRUYT	BE0974256852	COLR BB	Belgium	Euronext Brussels
FOUNTAIN	BE0003752665	FOU BB	Belgium	Euronext Brussels
GREENYARD	BE0003765790	GREEN BB	Belgium	Euronext Brussels
LOTUS BAKERIES	BE0003604155	LOTB BB	Belgium	Euronext Brussels
MIKO	BE0003731453	MIKO BB	Belgium	Euronext Brussels
SIPEF	BE0003898187	SIP BB	Belgium	Euronext Brussels
SPADEL	BE0003798155	SPA BB	Belgium	Euronext Brussels
TER BEKE	BE0003573814	TERB BB	Belgium	Euronext Brussels
PRFoods	EE3100101031	PRF1T ET	Estonia	Nasdaq Baltic Tallinn
RAISIO OYJ VAIHTO-OSAKE	FI0009002943	RAIVV FH	Finland	Nasdaq Nordic Helsinki
OLVI OYJ A	FI0009900401	OLVAS FH	Finland	Nasdaq Nordic Helsinki
HKSCAN OYJ A	FI0009006308	HKSAV FH	Finland	Nasdaq Nordic Helsinki
ATRIA OYJ A	FI0009006548	ATRAV FH	Finland	Nasdaq Nordic Helsinki
APETIT OYJ	FI0009003503	APETIT FH	Finland	Nasdaq Nordic Helsinki
ANORA GROUP OYJ	FI4000292438	ANORA FH	Finland	Nasdaq Nordic Helsinki
ADVINI	FR0000053043	ADVI FP	France	Euronext Paris
AGROGENERATION	FR0010641449	ALAGR FP	France	Euronext Paris
BONDUELLE	FR0000063935	BON FP	France	Euronext Paris
CARREFOUR	FR0000120172	CA FP	France	Euronext Paris
CASINO GUICHARD	FR0000125585	CO FP	France	Euronext Paris
DANONE	FR0000120644	BN FP	France	Euronext Paris
FINATIS	FR0000035123	FNTS FP	France	Euronext Paris
FLEURY MICHON	FR0000074759	ALFLE FP	France	Euronext Paris
FONCIERE EURIS	FR0000038499	EURS FP	France	Euronext Paris
KKO INTERNATIONAL	FR0013374667	ALKKO FP	France	Euronext Paris
LANSON-BCC	FR0004027068	ALLAN FP	France	Euronext Paris
LAURENT-PERRIER	FR0006864484	LPE FP	France	Euronext Paris
LDC	FR0013204336	LOUP FP	France	Euronext Paris
MALTERIES FCO-BEL	FR0000030074	MALT FP	France	Euronext Paris
MBWS	FR0000060873	MBWS FP	France	Euronext Paris
PERNOD RICARD	FR0000120693	RI FP	France	Euronext Paris

POULAILLON	FR0013015583	ALPOU FP	France	Euronext Paris
REMY COINTREAU	FR0000130395	RCO FP	France	Euronext Paris
SAINT JEAN GROUPE	FR0000060121	SABE FP	France	Euronext Paris
SAPMER	FR0010776617	ALMER FP	France	Euronext Paris
SAVENCIA	FR0000120107	SAVE FP	France	Euronext Paris
TIPIAK	FR0000066482	TIPI FP	France	Euronext Paris
UNIBEL	FR0000054215	UNBL FP	France	Euronext Paris
VOLMORIN & CIE	FR0000052516	RIN FP	France	Euronext Paris
Schwälbchen Molkerei	DE0007218901	SMB GR	Germany	Frankfurt Stock Exchange
Park & Bellheimer AG	DE0006902000	PKB GR	Germany	Frankfurt Stock Exchange
Schloss Wachenheim AG	DE0007229007	SWA GR	Germany	Frankfurt Stock Exchange
FRoSTA AG	DE0006069008	NLM GR	Germany	Frankfurt Stock Exchange
Südzucker	DE0007297004	SZU GR	Germany	Frankfurt Stock Exchange
KWS SAAT SE & Co. KGaA	DE0007074007	KWS GR	Germany	Frankfurt Stock Exchange
DONEGAL INVESTMENT	IE000TIRQBE1	DQ7A ID	Ireland	Euronext Dublin
GLANBIA PLC	IE0000669501	GLB ID	Ireland	Euronext Dublin
KERRY GROUP PLC	IE0004906560	KYGA ID	Ireland	Euronext Dublin
ORIGIN ENT. PLC	IE00B1WV4493	OGN ID	Ireland	Euronext Dublin
ORSERO	IT0005138703	ORS IM	Italy	Euronext Milan
VALSOIA	IT0001018362	VLS IM	Italy	Euronext Milan
ENERVIT	IT0004356751	ENV IM	Italy	Euronext Milan
BIOREA	IT0005387995	BIE IM	Italy	Euronext Milan
CAMPARI	IT0003849244	CPR IM	Italy	Euronext Milan
CENTRALE DEL LATTE D'ITALIA	IT0003023980	CLI IM	Italy	Euronext Milan
Amber Latvijas balzams	LV0000100808	BAL1R LR	Latvia	Nasdaq Baltic Riga
Vilkyškių pieninė	LT0000127508	VLP1L LH	Lithuania	Nasdaq Baltic Vilnius
Rokiškio sūris	LT0000100372	RSU1L LH	Lithuania	Nasdaq Baltic Vilnius
Pieno žvaigždės	LT0000111676	PZV1L LH	Lithuania	Nasdaq Baltic Vilnius
Linas Agro Group	LT0000128092	LNA1L LH	Lithuania	Nasdaq Baltic Vilnius
AUGA group	LT0000127466	AUG1L LH	Lithuania	Nasdaq Baltic Vilnius
Žemaitijos pienas	LT0000121865	ZMP1L LH	Lithuania	Nasdaq Baltic Vilnius
Amsterdam commod.	NL0000313286	ACOMO NA	Netherlands	Euronext Amsterdam
Corbion	NL0010583399	CRBN NA	Netherlands	Euronext Amsterdam
Forfarmers	NL0011832811	FFARM NA	Netherlands	Euronext Amsterdam
Heineken	NL0000009165	HEIA NA	Netherlands	Euronext Amsterdam
Heineken Holding	NL0000008977	HEIO NA	Netherlands	Euronext Amsterdam
IEX Group NV	NL0010556726	IEX NA	Netherlands	Euronext Amsterdam
Lucasbols	NL0010998878	BOLS NA	Netherlands	Euronext Amsterdam
SLIGRO Food group	NL0000817179	SLIGR NA	Netherlands	Euronext Amsterdam
J.MARTINS,SGPS	PTJMT0AE0001	JMT PL	Portugal	Euronext Lisbon
SONAE	PTSON0AM0001	SON PL	Portugal	Euronext Lisbon
BODEGAS RIOJANAS S.A.	ES0115002018	RIO SM	Spain	Madrid Stock Exchange

BORGES AGRICULTURAL & INDUSTRIAL	ES0105271011	BAIN SM	Spain	Madrid Stock Exchange
DEOLEO	ES0110047919	OLE SM	Spain	Madrid Stock Exchange
EBRO FOODS	ES0112501012	EBRO SM	Spain	Madrid Stock Exchange
NATURHOUSE HEALTH	ES0105043006	NTH SM	Spain	Madrid Stock Exchange
PESCANOVA	ES0169350016	PVA SM	Spain	Madrid Stock Exchange
VISCOFAN	ES0184262212	VIS SM	Spain	Madrid Stock Exchange

Appendix B: Variables construction

All the stock related information has been retrieved from Bloomberg and the Yahoo finance website.

CAPM market risk premium:

The CAPM risk premium is constructed as the Eurostoxx 600 daily return retrieved from Bloomberg (considered as the European benchmark in this thesis) minus the daily 1-year euro area yield for AAA government bonds (considered as the risk-free rate in this thesis) retrieved from the European Central Bank website[1].

Market capitalization:

The market capitalization is constructed as the daily share price of the firm times the current year firm number of shares outstanding[2].

Price to book ratio:

The price to book ratio is constructed as the firm daily share price divided by the firm annual book value per share[3].

Six-month momentum:

The sixth-month momentum is constructed as the firm previous month 6-month return in order to avoid an overlap with the short-term reversal effect as recommended by Hanauer (2020).

EBIT:

The EBIT is simply the firm current year EBIT value.

Assets growth:

The assets growth is computed as the firm current year assets value minus the firm prior year assets value.

[1] https://www.ecb.europa.eu/stats/financial_markets_and_interest_rates/euro_area_yield_curves/html/index.en.html

[2] The number of shares outstanding is defined as the number of shares issued minus the number of shares that are detained by the company.

[3] The book value per share is computed as the difference between the current year firm's common stockholder's equity and the current year firm's preferred equity, then divided by the current year firm's number of shares outstanding.

Net income:

The net income is simply the firm current year net income value.

Return on assets:

The return on assets is constructed as the firm current year net income value divided by the firm current year assets value.

Debt growth:

The debt growth is constructed as the firm current year long-term debt value minus the firm previous year long-term debt value.

Proportion of shares issuance:

The proportion of shares issuance is constructed as the difference between the firm current year number of outstanding shares and the firm prior year number of outstanding shares, then divided by the firm prior year number of shares outstanding.

Gross margin:

The gross margin is computed as the firm current year operating profit value divided by the firm current year sales value.

Assets turnover growth:

The firm assets turnover growth is constructed as the firm current year assets turnover ratio[4] minus the firm previous year assets turnover ratio retrieved from the Yahoo finance website.

Leverage:

The leverage is constructed through its debt to equity form, by dividing the firm current year total debt value by the firm current year common stockholder equity.

[4] The asset turnover ratio is computed as firm sales divided by this firm asset value.

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Executive summary

The 2020 covid-19 pandemic has been a historically exceptional situation through the impact it had on every aspect of the world we live in and financial markets have not been spared as the pandemic led to the biggest stock markets drop since the 2008 subprimes financial crisis. Lockdowns imposed by the pandemic had various and unforeseen impacts on the businesses depending on their ability to adapt to the exceptional situation or they characterization as essentials businesses or not. Even among the sectors historically classified as defensive, the resilience of some businesses has been severely tested. This never seen before situation offers a new opportunity to observe what are the factors explaining the stocks returns of firms from the historically defensive sectors.

This thesis tries to identify the factors explaining the stock returns of the European food and drinks listed companies during the covid-19 pandemic crisis. In order to do so a principal component analysis will be applied on firm characteristics historically used to explain stock returns in order to reduce the dimensionality of the data set in linear combinations of these characteristics called principal components. Then these principal components will be rotated using a varimax criterion to increase their economic interpretability and these rotated components will be used as risk factors and risk factors long short portfolios will be created to capture the returns associated to exposure to these risk factors. Finally, these long short portfolio returns will be used in a Fama-Macbeth regression in order to assess the premia linked to the risk factors exposure and their statistical significance.

The results of this thesis show that the classical impacting firm characteristics retrieved from the financial literature failed to explain the European food and drinks industry stock returns during the covid-19 pandemic.