Music Sentiment and Stock Returns in Sweden

Bachelor Thesis in Finance Fall 2024

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Abstract:

This study investigates the relationship between music sentiment, a novel proxy for investor sentiment, and stock returns in Sweden. We utilise Spotify data and calculate the stream weighted average valence (SWAV) for each week in our dataset to measure aggregate sentiment. This paper extends prior research by incorporating a longer time frame, firm-specific returns and cross-industry analysis to deepen the understanding of sentiment-driven dynamics. Our results reveal a significant positive relationship between music sentiment and concurrent stock returns on the market and firm level, with evidence of subsequent price corrections the following week. At the firm level, our findings reveal that this relationship is evident regardless of industry. Further cross sectional analysis indicate that riskier, high growth and financially distressed firms exhibit heightened sensitivity to sentiment. However, these findings cross sectional findings lack robustness and calls for further research. Sweden provides an ideal setting for this analysis, given its high retail investor participation and widespread Spotify usage, which enhance the reliability of sentiment as a market indicator.

Keywords:

Music Sentiment, Behavioural Finance, Investor Sentiment, Swedish Stock Market

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1 Introduction

Behavioural finance has emerged as a significant paradigm in economic theory, challenging the long-dominant Efficient Market Hypothesis (EMH). While EMH assumes that markets are rational and reflect all available information, behavioural finance highlights the role of psychological and behavioural biases in influencing market outcomes. This paradigm shift gained widespread recognition in 2017 when Richard Thaler, a pioneer in behavioural economics, was awarded the Nobel Prize in Economic Sciences for his contributions to understanding how human psychology shapes economic decision-making, particularly in areas like bounded rationality, mental accounting, and nudge theory.

Building on this foundation, previous research in behavioural finance consistently emphasizes the impact of investor sentiment and pricing anomalies on short-term stock market performance (Hirshleifer and Shumway, 2003; Edmans, Garcia and Norli, 2007; Tetlock, 2007; Cochrane, 2011). These findings challenge the predictions of EMH, which assumes market efficiency in pricing. In response, scholars have developed various sentiment measures to better account for observed market anomalies and the behavioural forces behind them.

Previous sentiment measures vary in their construction, with many focusing on external factors assumed to influence investor sentiment. For instance, Schmittmann et al. (2015) examine how weather shapes sentiment and trading behavior among German retail investors, while Birru (2018) explores the effects of day-of-the-week patterns on sentiment and return anomalies. Other approaches, such as those by Soo (2018) and Jiang et al. (2019), construct market sentiment indices based on qualitative tones in local housing news and corporate financial disclosures, respectively. Despite methodological differences, these approaches share common limitations. Many rely on subjective assessments of sentiment, such as analyzing positive or negative words in textual data, which introduces challenges related to linguistic interpretation and context. Additionally, external factors like weather and calendar effects may indirectly reflect investor mood rather than providing a direct measure of emotional states.

In response to these limitations, a novel proxy for sentiment has emerged - music (Edmans, Fernandez-Perez, Garel and Indriawan, 2021; Fernandez-Perez, Garel and Indriawan, 2020; Can, Le and Yu, 2023). Unlike approaches that focus on external factors assumed to influence sentiment, music sentiment functions as an endogenous indicator of a population's genuine emotional state through their music consumption patterns. Prior research demonstrates that individuals use music as a reflection of their mood. For example, North and Hargreaves (1996) find that participants' music preferences align with their current emotional state, Saarikallio and Erkkilä (2007) show that individuals express emotions by choosing sad music when feeling unhappy, and Hunter, Schellenberg and Griffith (2011) document the elimination of preferences for upbeat music when participants are induced into a downbeat mood.

Moreover, studies have revealed a correlation between music sentiment and economic indicators, as evidenced by Zullow's (1991) findings that the optimism in U.S. Top 40 songs can predict GNP growth and Sabouni's (2018) research linking music sentiment with the Michigan Consumer Index. Furthermore, Mehr, Singh, Knox, Ketter, Pickens-Jones, Atwood and Howard (2019), in their study of over 300 cultures across different periods, show that societies tend to use similar music in comparable contexts. Consequently, music sentiment provides a distinctive opportunity to adopt a language-independent, universally comparable, and endogenous measure of actual sentiment, addressing the limitations of previous sentiment measures.

In alignment with prior research methodologies, this study utilizes weekly Spotify data from Sweden's Top 200 list to estimate music sentiment through the metric of valence, developed by Spotify's subsidiary The Echo Nest. Valence quantifies the positivity associated with a song. To apply this measure throughout our sample period, we construct a stream-weighted average valence (SWAV) for each week. We then classify music sentiment as the weekly change in SWAV. To validate this sentiment measure, we replicate the validation approach of Edmans et al. (2021), regressing the weekly change in SWAV on established sentiment measures to test for significant correlation. Additionally, we gather weekly adjusted price data for both the OMXSPI (Stockholm All-Share) index and individual stocks listed during the sample period.

Our findings reveal a positive and statistically significant association between music sentiment and concurrent weekly stock returns on the OMXSPI Index, observable both at the index and firm levels. This relationship holds even after controlling for macroeconomic variables, implied volatility, prior returns, seasonal variations, and firm-specific characteristics. Consistent with previous literature, we also observe a negative and significant correlation between SWAV and subsequent week returns, suggesting a price correction mechanism. This apparent price correction is consistent with previous research (Zakamulin, 2024; Brown & Cliff, 2005) which builds upon the idea that irrational traders have no long lasting impact on asset prices, as they are eventually corrected by rational arbitrageurs. After grouping firms based on their respective industries, regression results show that music sentiment has a positive and significant relationship with the real estate, consumer staples, consumer discretionary, basic materials, financial, healthcare, technology, industrials and telecommunications industry. Our findings reveal that the effect of music sentiment on stock returns is evident in almost all industries and that no particular industry is driving the relationship.

Further cross-sectional analysis of stock returns within the OMXSPI index indicates that music sentiment exerts a more substantial influence on firms with high growth opportunities, financial distress, consistent with the framework proposed by Baker and Wurgler (2006). We also find that riskier stocks, measured by their market beta, are more sensitive to shifts in music sentiment. However, after investigating if the effect is significantly different across these cross sectional groups, we can conclude that our findings only offer weak support to this relationship.

2 Literature Review

Our research thesis builds upon and extends the foundational work of Edmans et al. (2021), which explores the relationship between music sentiment and stock returns across 40 countries from 2017 to 2020. Their findings demonstrate a positive and significant correlation between weekly changes in music sentiment and contemporaneous stock returns globally, after controlling for factors such as past returns, world market returns, seasonal effects, macroeconomic conditions, and weather patterns. Additionally, the study identifies a strong reversal effect in stock returns in the subsequent week, suggesting a price correction. Further, Edmans et al. (2021) document that music sentiment is positively correlated with net equity fund flows and inversely related to government bond returns, reinforcing the broader relevance of sentiment to market behavior.

Other key studies investigating the impact of music sentiment include Fernandez-Perez et al. (2020) and Can et al.(2023). Both studies, like our own, focus on country-specific contexts, examining the effects of music sentiment in the U.S. and Vietnam, respectively. Can et al. (2023) furthermore extends the analysis and investigates the effect of music sentiment across different industries, tough the findings remains somewhat inconclusive. Consistent with the findings of Edmans et al. (2021), these studies also report a positive and significant relationship between music sentiment and stock returns, underscoring the robustness of music sentiment as a predictor of market performance across different national contexts.

The ideal setting for this analysis would be a market where all stocks are traded exclusively by retail investors actively listening to music on Spotify, reflecting their mood in a way that could be used to predict their behavior. While no such market exists, we argue that Sweden provides a the optimal approximation to this ideal scenario.

Firstly, a study by Kaustia, Conlin, and Luotonen (2023) on stock market participation rates in European countries identifies Sweden as the leader, with a participation rate ranging from 60% to 70% between 2004 and 2013. During the same period, countries included in the global study by Edmans et al. (2021) reported significantly lower stock market participation rates. Mediterranean countries such as Italy and Spain recorded participation rates of approximately 10%, while Germany and the Netherlands reported rates just below 30%. Denmark and Switzerland ranked just behind Sweden, with rates of 50% to 60% and 40% to 50%, respectively. Furthermore, the United States, which was the focus of Fernandez-Perez et al. (2020), had a stock market participation rate ranging from 50% to 60% during this period.[1] Although data on Vietnam, the market analyzed in Can et al.'s study, is limited, figures from 2024 indicate that only 8% of the population are active investors, compared to approximately 40% in Sweden, as reported by Kaustia et al. (2023)[2]

Secondly, as the birthplace of Spotify, Sweden has a notably high number of Spotify users relative to its population size. According to Statista Market Insights, 66% of music streaming in Sweden is done via Spotify.[3] By comparison, Spotify's share of the global music streaming market, reflecting the sample in Edmans et al. (2021), is approximately 33%. In the United States, which Fernandez-Perez (2020) analyzed, Spotify holds a 29% share of streaming services, despite having the highest total number of Spotify users

[1] https://www.statista.com/statistics/270034/percentage-of-us-adults-to-have-money-invested-in-the-stock-market

[2] https://vietnamnews.vn/economy/1660169/vietnamese-stock-market-sees-remarkable-24-year-transformation.html

[3] https://www.statista.com/outlook/dmo/digital-media/digital-music/music-streaming/worldwide?currency=USDlocale=enusers

worldwide. In the UK, which has the most Spotify users in Europe, Spotify's share of music streaming services stands at 42%. Data on Vietnam, the market analyzed by Can et al. (2023), does not include specific figures on Spotify users in the country, as Spotify data for Vietnam was not reported in the Statista Market Insights. However, the same source indicates that only 3.3% of the Vietnamese population engages in music streaming. In contrast, 36% of the Swedish population uses streaming services, with 24% of the entire population using Spotify specifically.

Moreover, we have extended the time frame from January 2017 to September 2024. This allows us to capture a broader range of market movements and analyze the relationship between music sentiment and stock returns during periods of high uncertainty and significant fluctuations. We also study the impact of music sentiment on firm-specific returns, which enables an understanding of how sentiment-driven dynamics may affect individual companies, rather than just market-wide indices. We extend this approach and look at the correlation between music sentiment and returns across different industries, hoping to fill the gaps of Can et al. (2023) by studying a market with more favorable conditions. This approach also allows for an investigation into the cross-sectional effects of music sentiment on stock returns, which has not previously been explored.

3 Data

3.1 Valence

To assess the sentiment of music in Sweden, we examine the weekly top 200 songs on Spotify from January 5, 2017, to September 12, 2024. The Spotify charts, updated every Thursday, provide a range of metrics for each song, including "valence," a measure intended to capture the emotional positivity conveyed by a track. The valence data for this study was scraped using Spotify's API for Spotify charts. Valence is a metric developed by The Echo Nest, a subsidiary of Spotify, and is designed to reflect the perceived positivity of a song. The metric is derived through expert assessments of musical positivity, which have been utilized to train a machine learning algorithm[4]. This algorithm assigns each song a valence score on a scale from 0 to 1, with 1 indicating a highly positive emotional tone. It is worth noting that Spotify offers additional metrics, such as "energy" and "danceability," which could potentially capture aspects of a song's positivity. However, this study focuses on the valence measure, as it has been previously utilized in related research and is specifically designed to assess the emotional positivity of a song. This established use of valence provides a consistent and reliable basis for comparison across studies.

Furthermore, for each song included in the top 200 list, the number of weekly streams is reported. A stream is counted by Spotify if a song is listened to more than 30 seconds[5]. To measure the weekly aggregate sentiment in Sweden, we calculate the weighted average valence of the top 200 songs, with each song's valence weighted by its respective number of streams. This approach follows the methodology of Edmans et al. (2021), and we will henceforth refer to this measure as the Swedish Weighted Average Valence (SWAV). The

[4]https://web.archive.org/web/20170422195736/http://blog.echonest.com/post/66097438564/plotting-musics-emotional-valence-1950-2013

[5]https://support.spotify.com

formula for SWAV is as follows:

$$SWAV_t = \sum_{i=1}^{200} \left(\frac{\text{Streams}_{i,t}}{\sum_{i=1}^{200} \text{Streams}_{i,t}} \times \text{Valence}_{i,t} \right)$$

where $Streams_{i,t}$ is the total streams of song i at time t and $Valence_{i,t}$ is the valence of song i at time t.

We then classify music sentiment as the weekly change in SWAV (ΔSWAV) as follows:

$$\Delta SWAV = \text{SWAV}_t - \text{SWAV}_{t-1}$$

Figure 1 illustrates the fluctuations of SWAV over time. While a slight increase in SWAV is visible, the trend is weak, and recurring variations are evident throughout the study period, accompanied by differences in volatility. A notable seasonal pattern emerges, with SWAV peaking during the summer months and reaching its lowest levels in winter across all years.

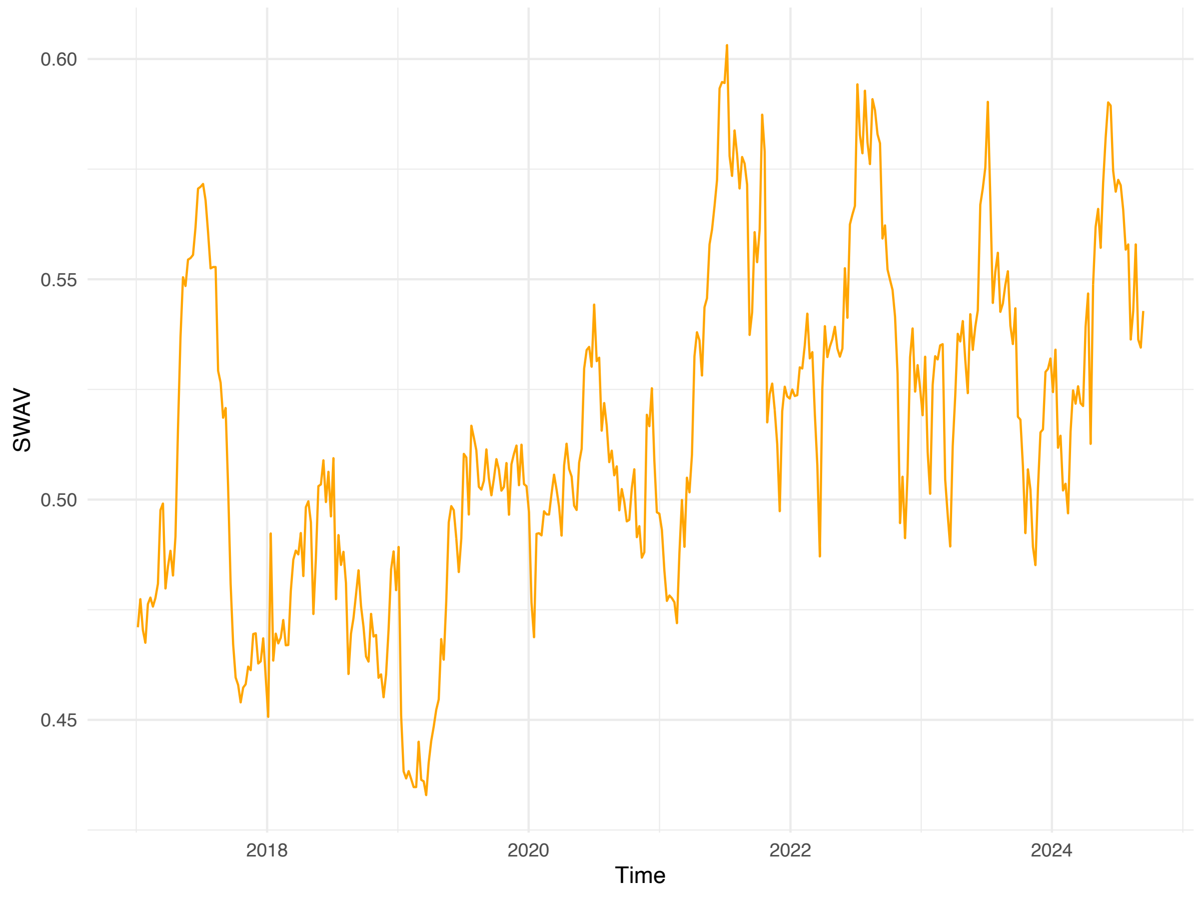

Figure 1: SWAV Over Time. This figure reports the weekly stream weighted average valence (SWAV) of the Spotify Top 200 list in Sweden from the 5th of January 2017 to the 12th of September 2024.

To further explore these seasonal patterns, we calculate the mean weekly change in SWAV for each month of every year during the study period, presented in Table 1. The results reinforce the visual pattern observed in Figure 1, as ΔSWAV is positive from February to June before turning negative, aligning with the observed peaks in summer and troughs in winter.

Table 1: Mean Weekly Music Sentiment by Month. This table shows the mean weekly music sentiment for every month of the year, as measured by the average weekly change in the stream weighted average valence (SWAV) of the Spotify Top 200 list in Sweden from the 5th of January 2017 to the 12th of September 2024

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
-0.00325	0.00189	0.00015	0.00465	0.00429	0.0033	-0.00099	-0.0029	-0.0045	-0.00295	0.00053	0.00048

This seasonal trend aligns with existing research on mood variations linked to physiological changes throughout the year. For instance, it has been demonstrated that cortisol levels, which play a key role in mood regulation, increase in winter, leading to reduced mood and energy during colder months (Sher, 2006). Conversely, lower cortisol levels during the summer are associated with improved mood and overall well-being. These findings underscore the significant impact of seasonal physiological changes on mood, providing a compelling basis for the observed peaks and troughs in SWAV across the seasons.

For further analysis, Figure 2 presents the yearly mean of music sentiment, measured as the weekly change in SWAV, across our sample period. In 2017, sentiment in Sweden reached its lowest point on record. Following this period, sentiment gradually increased, reaching a positive trajectory until 2020. In 2020, the first year of the COVID-19 pandemic, we can observe a steep decrease in sentiment with a negative mean change in SWAV. Post-2020, sentiment began to recover. Although a still positive change in average SWAV, sentiment showed a decline in 2022, the starting year of Russia's invasion of Ukraine. An increase in sentiment can be observed in 2023 and 2024.

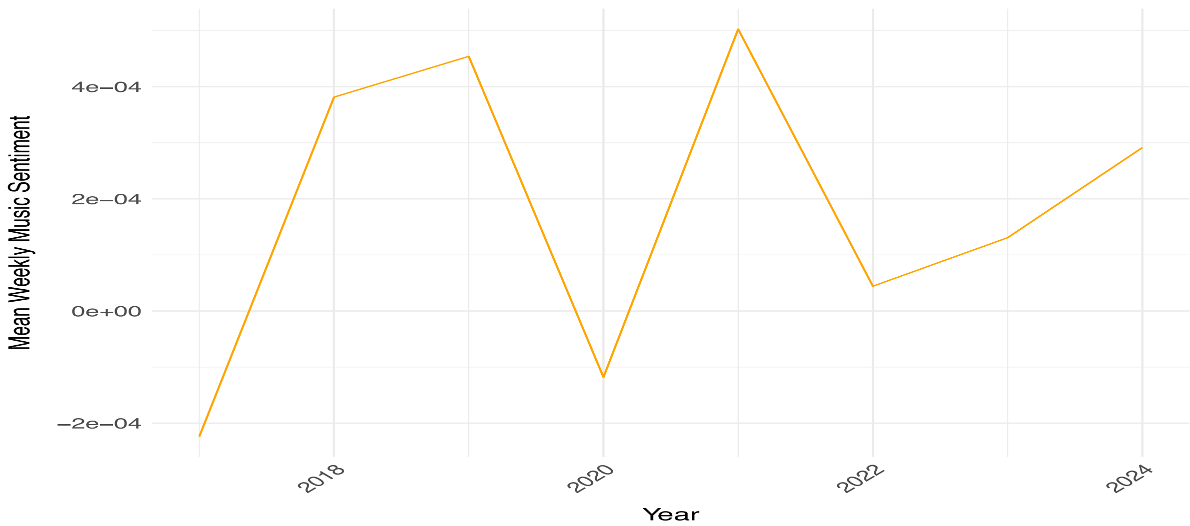

Figure 2: Mean Yearly Music Sentiment. This figure shows the mean yearly music sentiment for the year 2017-2024, as measured by the average weekly change in the stream weighted average valence (SWAV) of the Spotify Top 200 list in Sweden

3.2 Validation of Music Sentiment

To validate our sentiment-based measure, we employ the methodology developed by Edmans et al. (2021), adapting it specifically for Sweden. This approach examines the correlation between our sentiment-based measure and established indicators known to influence individuals' mood, to determine whether our sentiment proxy follows similar patterns.

Firstly, we expect music sentiment to be lower during seasonal periods associated with declining mood and higher during periods of improving mood. Previous research, including studies by Thaler (1987), Kamstra et al. (2017), and Hirshleifer, Jiang, and DiGiovanni (2020), and Sher (2006), highlights the influence of Seasonal Affective Disorder (SAD) on mood. SAD is a form of depression that occurs at specific times of the year, typically during autumn and winter, and is linked to reduced exposure to natural light. It often results in symptoms such as low energy, poor mood, and changes in sleep patterns, making it a key driver of seasonal mood variability. These studies reveal that different months exhibit varying levels of positivity or negativity in mood. While interpretations of seasonal effects differ across studies, we rely on the findings by Kamstra et al. to ensure comparability and uniformity with the validation methodology used by Edmans et al. (2021). Kamstra et al.'s findings suggests that January and March represent significant improvements in mood for countries in the Northern Hemisphere, coinciding with recovery from SAD. Conversely, September and October are associated with the peak prevalence of SAD and declines in mood. Based on these findings, we would expect a decrease in music sentiment during September and October and an increase during January and March.

Additionally, previous research has demonstrated that adverse weather conditions negatively affect mood, which in turn impacts same-day stock returns. For example, Hirshleifer and Shumway (2003) find that both mood and stock returns are higher on sunnier days, while Goetzmann, Kim, Kumar, and Wang (2015) show that increased cloud cover correlates with a greater propensity to sell among institutional investors. Thus, we expect that music sentiment will be inversely related to the degree of cloud cover. In alignment with Edmans et al. (2021), we collect hourly meteorological data through the National Oceanic and Atmospheric Administration's online database.[6] Specifically, we collect local hourly observations of cloud cover from the Arlanda Weather Station. These measurements are recorded on an integer scale ranging from 1 to 8 octas, where 1 represents nearly clear skies and 8 indicates complete overcast conditions. We utilize this data to compute the average cloud cover for each day within the period from January 5, 2017, to September 12, 2024. Given the seasonality inherent in cloud cover, we deseasonalize these values by subtracting each week's time-series mean from the corresponding daily averages, following the method proposed by Edmans et al. (2021) and Goetzman et al. (2015). For instance, consider the first week in our dataset, corresponding to the first calendar week of 2017. For this week, we calculate the average cloud cover across the first calendar week of each year from 2017 to 2024. We then subtract this weekly mean from all daily values within the corresponding week of 2017. This process yields the deseasonalized daily average change in cloud cover for the week, which we henceforth refer to as "CC".

Following the COVID-19 pandemic, emerging studies indicate that government-imposed restrictions have negatively impacted public mood (e.g P. Terry, Parsons-Smith and V. Terry, 2020; Bueno-Notival, Gracia-García, Olaya, Lasheras, López-Antón and Santabárbara, 2021). Following this, we expect to see a decrease in music sentiment when restrictions become more extensive. To track the evolution of such restrictions in Sweden over our sample period, we follow the methodology in Edmans et al. (2021) and use data of the University of Oxford's COVID-19 Government Response Stringency Index from the United Nations Office for the Coordination of Humanitarian Affairs (OCHA).[7] This initiative was aimed at collecting information on government policy aimed at tackling the pandemic. For the Swedish context, instead of compiling our own index like Edmans et.al (2021), we use the Oxford COVID-19 Government Response Stringency Index. This index is aimed to capture the degree of strictness in government imposed restrictions and is based on nine response indicators including school closures, workplace closures, and travel bans. The index ranges from 0 to 100, where 100 is the strictest. Furthermore, the index we use incorporates restrictions for both vaccinated and non-vaccinated people, while taking into account the weighted average of vaccinated and non-vaccinated people in the Swedish population.

We estimate the following linear regression model:

$$\begin{aligned} \mathit{Music\ Sentiment}_t = \alpha + \beta_1 \cdot \mathit{Positive\ Months}_t + \beta_2 \cdot \mathit{Negative\ Months}_t + \beta_3 \cdot \mathit{CC}_t \\ + \beta_4 \cdot \mathit{COVID}_t + \varepsilon_t \end{aligned} \tag{1}$$

where *Music Sentiment* is the weekly change in the stream weighted average valence (SWAV) of the Spotify Top 200 list in Sweden. *Positive Months* is a dummy variable assigned a value of 1 for January and March. *Negative Months* is a dummy variable assigned a value of 1 for the months September and October. *CC* denotes the weekly deseasonalized average daily change in cloud cover in Sweden and *COVID* is the weekly

[6]https://www.ncei.noaa.gov/access/search/dataset-search?text=cloud%20cover&bbox=69.060,11.113,55.340,24.167&place=Country:71&pageNum=1

[7]https://data.humdata.org/dataset/oxford-covid-19-government-response-tracker

change in Covid-19 related government imposed restrictions in Sweden, as measured by the weekly change in the University of Oxford's COVID-19 Government Response Stringency Index.

Table 2 reports regression estimates of Eq.(1). Column 1 includes the *Positive Months* and *Negative Months* dummy variables, with year fixed effects. In accordance with our hypothesis and previous research, we observe a significant negative correlation between negative months (i.e months with declining mood) and music sentiment at the 1% level. However, we also obtain a negative estimate for positive months (January and March), significant at the 10% level. This result aligns with the findings in Table 1, which show a strong negative mean music sentiment in January and only slightly positive sentiment in March.

Theoretically, months associated with an increase in mood should lead to a corresponding rise in music sentiment. However, Edmans et al. (2021) similarly report a negative estimate for months linked to improving mood. This suggests that seasonal patterns in music sentiment may deviate from the SAD effect associated with the specific months highlighted by Kamstra et al. (2017). While Kamstra et al.'s (2017) timing of specific months may not fully capture the nuances of music sentiment on a monthly basis, this does not negate the broader influence of seasonal mood variations on sentiment. Instead, music sentiment may better reflect mood fluctuations over extended seasonal periods, as suggested by Sher (2006), which links mood to physiological changes. These changes, such as elevated cortisol in winter and its decline in summer, align with the results in Table 1. While Kamstra et al. (2017)'s framework may not perfectly match the monthly timing of music sentiment, the broader influence of seasonal mood variations driven by factors like sunlight exposure remains plausible.

Column 2 shows the regression of music sentiment on the deseasonalized average daily change in cloud cover (CC). We can observe a negative correlation, significant at the 5% level. This is consistent with our expectations and previous studies on the impact of weather conditions on stock returns and investor behavior (Hirshleifer et al., 2003 and Goetzmann et al., 2015). Column 3 shows the weekly change in the Oxford COVID-19 Government Response Stringency Index regressed on our music sentiment measure. Just as we expected, it shows a negative correlation between sentiment and the degree of stringency of government imposed COVID restrictions. However, it should be noted that this finding is not significant and therefore this only presents weak evidence for this correlation. Column 4 includes all variables and show that the aforementioned relationships still holds when all variables are included in the same regression.

Table 2: OLS Linear Regression. Validation of Music Sentiment. Music Sentiment is the weekly change in the stream weighted average valence (SWAV) of the Spotify Top 200 list in Sweden. This table show the estimation results of Eq.(1) with month and year fixed effects. Positive Months is a dummy variable assinged a value of 1 for the months January and March. Negative Months is a dummy variable assigned a value of 1 for the months September and October. CC denotes the weekly deseasonalized average daily change in cloud cover in Sweden. COVID is the weekly change in Covid-19 related government imposed restrictions in Sweden, as measured by the weekly change in the University of Oxford's COVID-19 Government Response Stringency Index. The table shows the standard errors in parentheses. Constants are not reported.

	Dependent variable: Music Sentiment			
	(1)	(2)	(3)	(4)
Positive Months	-0.003^{*}			-0.003^{*}
	(0.002)			(0.002)
Negative Months	-0.005^{***}			-0.005^{***}
	(0.002)			(0.002)
CC		-0.006^{**}		-0.006^{**}
		(0.002)		(0.002)
COVID			-0.001	-0.001
			(0.002)	(0.002)
Year Fixed Effects	Yes	No	No	Yes
Month Fixed Effects	No	Yes	Yes	No
Observations	401	401	401	401
R^2	0.029	0.079	0.063	0.045
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

3.3 Stock Market Returns

To measure the performance of the Swedish stock market during the study period, we obtain weekly adjusted closing prices from Refinitiv Datastream, covering Fridays from January 6, 2017, to September 13, 2024. We focus on the OMXSPI Index, also referred to as the Stockholm All-Share Index, which encompasses all stocks listed on the OMX Nordic Exchange Stockholm. The index values are adjusted to account for corporate actions such as rights issues, dividends, stock splits, and mergers or acquisitions. These adjustments ensure that our return calculations accurately capture the true economic gains or losses realized by investors, thereby isolating the effects of investor sentiment from other market dynamics.

Moreover, for each week in our sample period, we collect adjusted closing prices on Friday for every stock listed on OMXSPI during that particular week. As a result, the number of stock price observations varies across weeks. In total, 475 companies were listed on this exchange at some point during our study period. Like the index prices, individual stock prices are adjusted for corporate actions such as rights issues, dividends, stock splits, and mergers or acquisitions.

From these prices, we calculate weekly returns for the OMXSPI Index and all individual companies in our sample.

3.4 Control Variables

In our econometric models, we have opted to use control variables that are either specific to Sweden or as closely aligned with Swedish conditions as possible, to better capture country-specific effects. For one, we use past-week returns (PR) to control for autocorrelation in the weekly returns. Moreover, we control for the European Economic Policy Uncertainty Index (EPU) to capture effects of fiscal, monetary and regulatory changes on returns. We also account for the V2TX Index (VIX) which captures the implied volatility of the EURO STOXX 50 Index and thus market expectations on future volatility. Furthermore, we include the macroeconomic index from the Swedish Statistical Central Bureau's survey (Macro Index) to capture changes in macroeconomic condtions and the deseasonalized change in cloud cover (CC) since it is correlated with both music sentiment and returns (Hirshleifer Shumway, 2003).

Alongside these control variables, we incorporate additional firm-specific characteristics since part of our analysis revolves around music sentiments effect on individual firms. This is pivotal in order to control for firm-specific characteristics which are known to impact returns and isolate the effect of sentiment. In total, our sample contain 475 unique company stocks. For firm-specific control variables, we use market value (MV), given by the shares outstanding times the current share price , which has been proven to influence the cross section of stock returns (e.g. Fama and French, 1992; Banz, 1981). As the performance of a stock is tied to the company's financial performance we control for the 12-month return on equity (ROE) and 12-month sales growth (SG). As previous studies have found capital structure to have a significant on stock returns (e.g. Murado˘glu and Sivaprasad, 2012; Strong and Xu, 1997) we control for the 12-month debt-to-assets ratio (DA). All firm-specific control variables are sourced from Refinitiv Datastream.

3.5 Sample Statistics

Table 3: Summary Statistics. This table show descriptive statistics for all of the data used in our paper during our sample period. SWAV is the stream weighted average valence of the Spotify Top 200 list in Sweden. Macro Index is the Swedish Statistical Central Bureau's Macroeconomic Index. VIX is the value of the V2TX Index, measuring the implied volatitliy of the EURO STOXX 50 Index. EPU is the value of the European Economic Policy Uncertainty Index (EPU). CC is the average daily change in deseasonalized cloud cover in Sweden. RET is the return of the OMXSPI Index. COVID is daily value of the Oxford COVID-19 Government Response Stringency Index. FIRM RET is the company specific returns of all stocks listed on the OMXSPI Index during our sample period. DA is the annual debt-to-assets ratio of each firm in our sample. EXTF is the annual external financing-to-assets ratio of each firm in our sample. BTM is the book-to-market value of equity ratio of each firm in our sample. BETA is the historical market beta of each firm in our sample. SG is the annual sales growth of each firm in our sample. ROE is the annual return on equity for each firm in our sample. MV is the market value of each firm in our sample.

	Observations	Mean	StdDev	Min	Max
SWAV	402	0.514	0.037	0,433	0.603
MACRO INDEX	92	95.393	9.619	77.900	113.200
VIX	401	19.522	7.854	10.690	74.330
EPU	92	254.184	61.833	135.164	418.619
CC	401	0.003	0.269	-0.940	0.812
RET	401	0.002	0.026	-0.172	0.080
COVID	2,813	14.295	23.404	0	71.130
FIRM RET	157,685	0.002	0.074	-0.984	7.263
DA	157,622	0.334	0.312	-0.541	7.312
EXTF	152,884	0.058	0.254	-5.046	3.122
BTM	158,867	0.691	1.755	-9.091	100
BETA	451	1.027	0.462	-0.800	2.700
SG	155,571	0.497	7.966	-1	349.846
ROE	155,427	0.024	0.912	-28.311	12.482
MV	174,014	25,873.870	94,921.820	0	2,749,415

4 Empirical Analysis and Results

4.1 Music Sentiment and Stock Market Returns in Sweden

In our first analysis, we investigate the relationship between music sentiment and stock market returns in Sweden. Given findings in previous research (Edmans et al., 2021; Fernandez-Perez at al., 2020), we expect that an increase in music sentiment should lead to higher stock market returns the same week, followed by lower returns the next week. To test this, we estimate the following linear regression:

$$Return_t = \alpha + \beta_1 \cdot Music\ Sentiment_t + \beta_n \cdot Controls_{n,t} + \varepsilon_t \tag{2}$$

where $Return_t$ is the weekly adjusted return of the OMXSPI Index at time t, $Music\ Sentiment_t$ is the contemporaneous weekly change in the stream weighted average valence of the Spotify Top 200 list in Sweden at time t and $Music\ Sentiment_{t-1}$ is the one week lagged music sentiment. *Controls* include all of our control variables. We control for the past week returns of the OMXSPI Index (PR), the weekly change of European

Economic Policy Uncertainty Index (EPU), the weekly value of the VSTOXX50 Index (VIX), the weekly change in the Swedish Statistical Central Bureau's Macroeconomic Index (Macro Index), the average daily change in deseasonalized cloud cover for the week (CC) and month fixed effects.

Furthermore, to investigate the relationship between music sentiment and next week returns, we estimate a regression:

$$Return_t = \alpha + \beta_1 \cdot Music\ Sentiment_{t-1} + \beta_n \cdot Controls_{n,t} + \varepsilon_t \tag{3}$$

where $Music\ Sentiment_{t-1}$ represents music sentiment lagged by one week. Due to lack of observations in our model, we do not winsorize our data as Edmans et al. (2021) did.

Table 4 reports the results of Eq. (2) and (3). Column 1 shows the results for Eq. (2) where we can observe a positive relationship between music sentiment and contemporaneous returns on the OMXSPI index, significant at the 10% level. The magnitude of the estimate (0.2) suggests that a one standard deviation increase in music sentiment leads to a 0.74% higher return the same week. Column 2 reports the results of Eq.(3), which indicate a negative correlation between one-week lagged music sentiment and OXSPI returns, significant at the 1% level. This implies that an increase in music sentiment one week is followed by a 1.15% lower return in the subsequent week, reflecting a potential reversal effect of sentiment-driven market movements. This pattern indicates a price correction, consistent with previous literature demonstrating that asset prices tend to revert following periods of elevated sentiment (e.g., Zakamulin, 2024; Brown & Cliff, 2005). However, it should be noted that the standard errors in our models are relatively large compared to our estimates which introduces uncertainty around the estimated effects.

Examining the control variables in both models, we observe that past week returns are negatively correlated with current returns. This suggest a negative serial correlation between returns, altough it is not statistically significant (p-value=15,9% in model 1). We also find a negative correlation between EPU and stock market returns, suggesting that an increase in economic uncertainty negatively affect returns. However, this relationship is not statistically significant in our model (p-value=32,9% in model 1). Furthermore, our models shows that the implied volatility of the EURO STOXX 50 Index (VIX) is negatively correlated with returns on the swedish stock market, significant at the 1% level. This implies that when market expectations on future volatiltiy increases, contemporaneous returns decrease. The survey based Macroeconomic Index (Macro Index) is positively correlated with returns, suggesting that a more positive view on the Swedish economy is related to higher returns. Though, this relationship is not statistically significant in our model (p-value=16,9% in model 1). Lastly, cloud cover (CC) is negatively associated with returns, altough it is not statistically significant (p-value=18% in model 1). This implies that an increase in cloud cover over the week leads to lower returns, giving weak support to findings in previous literature.

Table 4: OLS Linear Regression: Music Sentiment and OMXSPI Returns. Column 1 in this table shows the estimation results of Eq.(2) and column 2 the results of Eq.(3). Dependent variable is weekly return of the OMXSPI Index. Music Sentiment is the contemporaneous weekly change of the stream weighted average valence on the Spotify Top 200 list in Sweden. Music Sentiment (t-1) is the one week lagged music sentiment. PR is the past week return of the OMXSPI Index. Macro Index is the Swedish Statistical Central Bureau's Macroeconomic Index. VIX is the value of the V2TX Index, measuring the implied volatitliy of the EURO STOXX 50 Index. EPU is the value of the European Economic Policy Uncertainty Index (EPU). CC is the average daily change in deseasonalized cloud cover in Sweden. The table shows the standard errors in parentheses. Constants are not reported.

	Dependent variable: OMXSPI Returns	
	(1)	(2)
Music Sentiment	0.200^{*}	
	(0.110)	
Music Sentiment (t-1)		-0.312^{***}
		(0.110)
PR	-0.072	-0.060
	(0.051)	(0.051)
EPU	-0.0001	-0.0001
	(0.0001)	(0.0001)
VIX	-0.001^{***}	-0.001^{***}
	(0.0002)	(0.0002)
Macro Index	0.0003	0.0004
	(0.0002)	(0.0002)
CC	-0.006	-0.007
	(0.005)	(0.005)
Month Fixed Effects	Yes	Yes
Observations	401	400
R^2	0.105	0.116
Note:		*p<0.1; **p<0.05; ***p<0.01

Tables 11 and 12 in the Appendix present robustness checks for the estimation of Eq. (2) and Eq. (3). In Table 11 we include year-month fixed effects instead of month fixed effects to ensure results are not driven by unobserved time-varying factors and find that it still holds. However, the effect of music sentiment on returns for the following week becomes statistically insignificant. In Table 12 we include contemporaneous and lagged music sentiment and in the same regression with and without controls, to ensure that the distinct contributions of each are accurately estimated. Both with and without control variables, we obtain similar results as before. However, our findings reveal that contemporaneous music sentiment is insignificant with controls. This could suggest that lagged music sentiment has a greater explanatory power, tough it might also be a consequence of a relatively low sample size.

4.2 Music Sentiment and Company Returns in Sweden

In the next step of our empirical analysis, we investigate the relationship between music sentiment and firm-level returns. More specifically, we examine how the returns of individual stocks within the OMXSPI Index relate to music sentiment. Since the returns of these constituents collectively drive the performance of the index, they are expected to correlate with the overall index returns. Furthermore, if sentiment influences the majority of stock returns in a similar direction, we would expect to observe a comparable relationship in a firm-level regression as we did with market-level returns.

To test this, we obtain weekly adjusted prices from Refinitiv Datastream and calculate weekly returns for all stocks listed on the Stockholm Stock Exchange at that point from January 6th, 2017, to September 13th, 2024.

Following the methodology of Edmans et al. (2021), we winsorize all variables at the 2.5% and 97.5% levels and subsequently estimate the following panel regressions:

$$\begin{aligned} \mathit{Return}_{i,t} &= \alpha + \beta_1 \cdot \mathit{Music\ Sentiment}_t + \beta_n \cdot \mathit{Controls}_{n,t} \\ &+ \beta_{n,i,t} \cdot \mathit{Firm\ Controls}_{n,i,t} + \varepsilon_{i,t} \end{aligned} \tag{4}$$

$$\begin{aligned} \mathit{Return}_{i,t} &= \alpha + \beta_1 \cdot \mathit{Music\ Sentiment}_{t-1} + \beta_n \cdot \mathit{Controls}_{n,t} \\ &+ \beta_{n,i,t} \cdot \mathit{Firm\ Controls}_{n,i,t} + \varepsilon_{i,t} \end{aligned} \tag{5}$$

where $\mathit{Return}_{i,t}$ is the weekly adjusted return of the company i at time t.
$\mathit{Music\ Sentiment}_t$ is the contemporaneous weekly change in the stream weighted average valence of the Spotify Top 200 list in Sweden. $\mathit{Music\ Sentiment}_{t-1}$ in Eq. (5) is the one-week-lagged music sentiment. *Controls* include our control variables. We control for the past week returns of the OMXSPI Index (PR), the weekly change of European Economic Policy Uncertainty Index (EPU), the weekly value of the VSTOXX50 Index (VIX), the weekly change in the Swedish Statistical Central Bureau's Macroeconomic Index (Macro Index) and the average daily change in deseasonalized cloud cover for the week (CC). *Firm Controls* are firm-specific characteristics known to affect returns: the 12-month return on equity (ROE), 12-month sales growth (SG), market value (MV) and the 12-month Debt-to-assets ratio (DA). We use firm and time fixed effects in both models.

Table 5 reports estimation results from Eq.(4) and (5), with firm and month fixed effects. Column 1 show the results of Eq. (4) revealing a positive relationship between music sentiment and same week company returns, significant at the 1% level. Specifically, a one standard deviation increase in music sentiment is associated with a 0.68% higher return the same week. Thus, the effect of music sentiment on returns is observable on both market level and firm level, suggesting that music sentiment impacts the majority of stock prices in the same direction. Examining Column 2, which presents the results of Eq. (5), we observe that music sentiment is again negatively correlated with next-week returns, significant at the 1% level. The negative estimate suggests that a one standard deviation increase in music sentiment one week is followed by a 1.11% lower return the following week. This is consistent with the theory of sentiment not having any lasting effect on asset prices and that they eventually return to their fundamental values. Examining the control variables, we observe that company returns on the OMXSPI Index is positively correlated with the past week market returns, significant at the 1% level in our lagged model, although it is not insignificant in our concurrent model. This is not consistent with our previous finding of a negative relationship with market-level returns. Moreover, stock specific returns is positively correlated with increases in economic policy uncertainty and negatively correlated with the implied volatility of the EURO STOXX 50 Index (VIX), positively correlated with improved macroeconomic conditions and negatively correlated with increased cloud cover. All of these relationships are significant at the 1% level. Examining the company specific controls, we observe that market value has no significant impact on stock returns, inconsistent with previous research findings. Return on equity is positively correlated with stock returns, significant at the 5% level. Sales growth is positively correlated with returns, but statistically insignificant. Debt-to-assets ratio is positively correlated with returns, significant at the 10% level in our contemporaneous model and at the 5% level in our lagged one.

Table 5: Panel Regression: Company Returns and Music Sentiment. Column 1 in this table show the estimation results of Eq.(4) and column 2 the results of Eq.(5). Dependent variable is company specific returns of our sample firms. Music Sentiment is the contemporaneous weekly change of the stream weighted average valence on the Spotify Top 200 list in Sweden. Music Sentiment (t-1) is the one week lagged music sentiment. PR is the past week return of the OMXSPI Index. Macro Index is the Swedish Statistical Central Bureau's Macroeconomic Index. VIX is the value of the V2TX Index, measuring the implied volatitliy of the EURO STOXX 50 Index. EPU is the value of the European Economic Policy Uncertainty Index (EPU). CC is the average daily change in deseasonalized cloud cover in Sweden. MV is the market value of each sample firm. ROE is the annual return on equity for each sample firm. SG is the annual sales growth for each sample firm. DA is the annual debt-to-assets retio of each sample firm. The table shows the standard errors in parentheses. Constants are not reported

	Dependent variable: Company Returns	
	(1)	(2)
Music Sentiment	0.183***	
	(0.013)	
Music Sentiment (t-1)		−0.299***
		(0.013)
PR	0.08	0.019***
	(0.006)	(0.006)
EPU	0.00004***	0.00002**
	(0.00001)	(0.00001)
VIX	−0.001***	−0.001***
	(0.00002)	(0.00002)
Macro Index	0.002***	0.003***
	(0.0001)	(0.0001)
MV	0.00000***	0.00000***
	(0.000)	(0.000)
ROE	0.011**	0.011**
	(0.001)	(0.001)
SG	0.0002	0.0002
	(0.0005)	(0.0005)
DA	0.003*	0.003**
	(0.001)	(0.001)
CC	−0.008***	−0.008***
	(0.001)	(0.001)
Fixed effects	Firm,Month	Firm,Month
Observations	138,306	137,839
R^2	0.013	0.015
Note:		*p<0.1; **p<0.05; ***p<0.01

For the estimation of Eq.(4) and (4), we conduct robustness checks to establish validity of the observed relationship (Table 13 and 14 in Appendix). First, we include year-month fixed effects instead of month fixed effects and find that the relationship remains consistent. Furthermore, we incorporate both contemporaneous music sentiment and a one-week lagged sentiment in the same regression. Whether control variables are included or excluded, the results remain similar to the original findings.

4.3 Music Sentiment and Company Returns by Industry

To deepen our understanding, we now investigate whether the relationship between music sentiment and stock returns observed at the broader market level is driven by specific sectors or parts of the market. For this purpose, all constituents of the OMXSPI Index are grouped into sector categories based on their respective established sector indices. Specifically, we analyze the real estate (SX35PI Index), consumer staples (SX45PI Index), consumer discretionary (SX40PI Index), basic materials (SX55PI Index), financials (SX30PI Index), healthcare (SX20PI Index), technology (SX10PI Index), industrials (SX50PI Index), telecom (SX15PI Index), energy (SX60PI Index), and utilities (SX65PI Index) sectors. Due to the limited number of firms included in the energy and utilities indices, and given the similar characteristics of companies in these sectors, these two groups are combined into a single category for this analysis.

Table 6 presents the estimation results for all industries. A positive correlation between music sentiment and company returns is observed across all industries, though the levels of statistical significance vary. The relationship is significant at the 1% level in all industries except for the energy and utilities sector and the healthcare industry. For the grouped energy and utilities sector, no statistical significance is found below the 10% level, while the healthcare industry shows significance at the 10% level. Thus, the positive and significant relationship between music sentiment and company returns is evident across almost all industries within the OMXSPI Index. While there are some differences in the magnitude of the SWAV coefficient, there is no evidence to suggest that any particular industry is solely driving the relationship. These findings, are similar to the ones made in Can et al. (2023) which investigates the relationship between music sentiment and industry returns on the Vietnamese stock market. While the paper finds a significant relationship between music sentiment and returns in the real estate, communication services, consumer discretionary, consumer staples, energy, financial, healthcare, information technology and utilities industry the sign of the relationships varies across different stock exchanges. Given this, the findings in the paper are somewhat inconclusive and we can offer some new empirical evidence on the relationship between investor sentiment, as measured by music sentiment, and the returns across different industries.

Table 6: Company Returns and Music Sentiment per Industry. This table show the estimation results for Eq.(4) for the companies in each industry. RE denotes real estate (SX35PI Index), S denotes con- sumer staples (SX45PI Index), D denotes consumer discretionary (SX40PI Index), B denotes basic materials (SX55PI Index), F denotes financials (SX30PI Index), H denotes healthcare (SX20PI Index), T denotes technology (SX10PI Index), I denotes industrials (SX50PI Index), TEL denotes telecom (SX15PI Index), E denotes energy (SX60PI Index) and utilities (SX65PI Index).

	Dependent variable: Industry Company Returns									
	(RE)	(S)	(D)	(B)	(F)	(H)	(T)	(I)	(TEL)	(E)
Music Sentiment	0.29***	0.25***	0.25***	0.23***	0.25***	0.15*	0.22***	0.27***	0.36***	0.2
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,153	3,189	19,146	9,663	11,848	19,445	11,350	30,608	4,590	2,263
R^2	0.023	0.042	0.019	0.028	0.043	0.063	0.020	0.032	0.029	0.024

Note: *p<0.1; **p<0.05; ***p<0.01

4.4 Music Sentiment and the Cross Section of Returns

We extend our analysis to examine the relationship between music sentiment and the cross-section of returns on the Stockholm All-Share Index. One of the most prominent studies that have examined the relationship between investor sentiment and the cross section of returns is Baker and Wurgler (2006). This study finds that firms with high book-to-market values of equity, often indicative of financial distress, have higher subsequent returns following periods of low sentiment. This suggests that these stocks, being more sentiment prone, become undervalued during periods of uncertainty which causes them to earn higher consecutive returns as their prices bounce back. Among other findings, the study also finds that firms with a high degree of external financing to assets, often indicative of speculation and high growth opportunities, tend to have lower returns following periods of high sentiment. This implies that these firms become overvalued when optimism is high and that the prices revert when sentiment is low. Drawing on these findings, we hypothesize that firms with high book-to-market values of equity and high degree of external financing to assets will be more sensitive to fluctuations in sentiment. Additionally, we hypothesize that firms with high leverage, measured by debt-to-assets, will be more sensitive to changes in sentiment as high levels of debt can be indicative of financial distress. Moreover, Antoniou, Doukas and Subrahmanyam (2014) find that high market beta stocks become overpriced during periods of high sentiment, as unsophisticated and overconfident investors take on risky investments. Therefore, we also expect stocks with high betas to be sentiment prone .

To test these hypotheses, we gather yearly financial data for all of our sample firms using Refinitiv Datastream. Namely, we collect total assets in MSEK, external financing (net issuance of debt and net issuance of equity) in MSEK, book and market value of equity in MSEK, and level of debt in MSEK for each company each year. Moreover, we collect the historical market beta of each stock in our sample. We then calculate the Book-to-market value of equity ratio, debt-to-assets ratio, external financing-to-assets ratio. Based on these proxies, we divide our sample stocks into tertiles each week to account for any new listings or delistings of constituents of the OMXSPI. Each grouping of stocks based on one of these metrics is conducted independently from the others. We divide our sample stocks into three distinct groups based on each financial metric: small (bottom 33rd percentile), medium (middle 33rd percentile), and large (top 33rd percentile). For each week, we then construct equally weighted portfolios of the stocks within each tertile and calculate weekly portfolio returns over our sample period. Subsequently, we use the same control variables as prior models, winsorize our grouping variables at the 2,5% and 97,5% levels and and estimate the following linear regressions for each proxy:

$$Small\ Group\ Returns_t = \alpha + \beta_1 \cdot Music\ Sentiment_t + \beta_n \cdot Controls_{n,t} + \varepsilon \tag{6}$$

$$Medium\ Group\ Returns_t = \alpha + \beta_1 \cdot Music\ Sentiment_t + \beta_n \cdot Controls_{n,t} + \varepsilon \tag{7}$$

$$Large\ Group\ Returns_t = \alpha + \beta_1 \cdot Music\ Sentiment_t + \beta_n \cdot Controls_{n,t} + \varepsilon \tag{8}$$

We use the same control variables as previous models (see Eq.2-5) and include month fixed effects.

Table 7 shows the estimation results of Eq. (6)-(8) grouped by the book-to-market value of equity ratio (BTM). Column 1 presents the Small Group regression, Column 2 the Medium Group regression, and Column 3 the Large Group regression. Our findings reveal that music sentiment is positively correlated with equally weighted portfolio returns across all size groups. Examining the table from left to right, we observe a gradual increase in the estimated coefficient for music sentiment, suggesting that stocks with higher book-to-market (BTM) ratios exhibit greater sensitivity to changes in sentiment. Specifically, for the large group, a one standard deviation increase in music sentiment is associated with a 0.83% higher portfolio return during the corresponding week. For the medium and small group portfolios, the same increase corresponds to a 0.74% and 0.48% higher return, respectively. The relationship is significant at the 5% level for the large group, at the 10% level for the medium group, while the small group exhibits a weaker correlation with no significance below the 10% level.

This finding aligns with previous research suggesting that stocks with higher BTM ratios are more sentiment-prone. The differing levels of statistical significance can be interpreted both as a limitation and a strength. On the one hand, the stronger significance for the medium and large groups supports the theory that higher BTM stocks are more sentiment-prone. On the other hand, the weaker significance for the small group suggests caution in drawing definitive conclusions, as the results may be influenced by noise or insufficient sample size in this category.

It should be noted that our model has standard errors that are large compared to our estimates and that introduces a significant margin of error in our model. For a robustness check, we conduct a two-sided Wald test to determine whether the music sentiment estimate for the large group portfolio is significantly larger than that of the small group. The test shows no statistical significance, indicating that the observed differences in sentiment sensitivity between the groups are not statistically meaningful. Our findings, therefore, provide only weak support for previous research findings.

Table 7: OLS Linear Regression: Cross Sectional Returns - BOOK TO MARKET RATIO. Column 1 show the estimation results of Eq.(6), column 2 show the results of Eq.(7) and column 3 the result of Eq.(8), grouped by book-to-market value of equity. Dependent variable is weekly return of the group portfolios. Music Sentiment is the contemporaneous weekly change of the stream weighted average valence on the Spotify Top 200 list in Sweden. Controls include: The past week return of the OMXSPI Index, the Swedish Statistical Central Bureau's Macroeconomic Index, the value of the V2TX Index, measuring the implied volatitliy of the EURO STOXX 50 Index, the value of the European Economic Policy Uncertainty Index and the average daily change in deseasonalized cloud cover in Sweden. The table shows the standard errors in parentheses. Constants are not reported.

	Dependent variable: Portfolio Returns		
	(1)	(2)	(3)
Music Sentiment	0.130	0.200^{*}	0.224^{**}
	(0.115)	(0.102)	(0.106)
Controls	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Observations	401	401	401
R^2	0.095	0.127	0.155
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 8 presents the estimation results of Eq. (6)-(8), grouped by debt-to-assets ratio (DA). Column 1 presents the Small Group regression, Column 2 the Medium Group regression, and Column 3 the Large Group regression. Our findings reveal that music sentiment is positively correlated with equally weighted portfolio returns across all groups, though the relationship is statistically significant only for the large group at the 5% level. Examining the table from left to right, we observe a gradual increase in the estimated coefficient for music sentiment, suggesting that stocks with higher debt-to-assets (DA) ratios are relatively more sentiment-prone. Specifically, for the small group, a one standard deviation increase in music sentiment is associated with a 0.36% higher portfolio return during the corresponding week. For the medium group, the same increase corresponds to a 0.68% higher return, while for the large group, it is associated with a 0.91% higher return.

This finding aligns with previous research suggesting that financially distressed stocks are more sentiment-prone. However, the varying levels of statistical significance across groups and the large standard errors indicate that while the trend is consistent, the relationship lacks robustness.

For a robustness check, we conduct a two sided Wald-test to test if the music sentiment estimate for the large group portfolio is significantly larger than the one of the small group. The test shows no statistical significance and our findings thus only give weak support to previous research findings.

Table 8: OLS Linear Regression: Cross Sectional Returns - DEBT TO ASSETS RATIO. Column 1 show the estimation results of Eq.(6), column 2 show the results of Eq.(7) and column 3 the result of Eq.(8), grouped by debt-to-assets ratio. Dependent variable is weekly return of the group portfolios. Music Sentiment is the contemporaneous weekly change of the stream weighted average valence on the Spotify Top 200 list in Sweden. Controls include: The past week return of the OMXSPI Index, the Swedish Statistical Central Bureau's Macroeconomic Index, the value of the V2TX Index, measuring the implied volatitliy of the EURO STOXX 50 Index, the value of the European Economic Policy Uncertainty Index and the average daily change in deseasonalized cloud cover in Sweden. The table shows the standard errors in parentheses. Constants are not reported

	Dependent variable: Portfolio Returns		
	(1)	(2)	(3)
Music Sentiment	0.098	0.183	0.247**
	(0.130)	(0.116)	(0.113)
Controls	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Observations	401	378	396
R^2	0.083	0.132	0.144
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 9 presents the estimation results of Eq. (6)-(8), grouped by external financing-to-assets ratio (EXTF). Column 1 presents the Small Group regression, Column 2 the Medium Group regression, and Column 3 the Large Group regression. Our findings reveal that music sentiment is positively correlated with equally weighted portfolio returns across all size groups, significant at the 10% level for the small group portfolio and at the 5% level for the medium and large group portfolios. Examining the table from left to right, we observe a gradual increase in the estimated coefficient for music sentiment, suggesting that stocks with higher EXTF ratios are relatively more sentiment-prone. Specifically, for the large group, a one standard deviation increase in music sentiment is associated with a 1.08% higher portfolio return during the corresponding week. For the medium and small group portfolios, the same increase corresponds to a 0.75% and 0.7% higher return, respectively.

This finding aligns with previous research suggesting that stocks with high growth opportunities, as measured by their degree of external financing, are more sentiment-prone. However, given the levels of statistical significance of our estimates, our findings do not offer robust support for this relationship.

Same as previous models, we have large standard errors for our estimates. For a robustness check, we conduct a two-sided Wald test to determine whether the music sentiment estimate for the large group portfolio is significantly larger than that of the small group. The test shows no statistical significance, indicating that the observed differences in sentiment sensitivity between the groups are not statistically meaningful. Consequently, our findings provide only weak support for previous research findings.

Table 9: OLS Linear Regression: Cross Sectional Returns - EXTERNAL FINANCING TO ASSETS. Column 1 show the estimation results of Eq.(6), column 2 show the results of Eq.(7) and column 3 the result of Eq.(8), grouped by external financing-to-assets ratio. Dependent variable is weekly return of the group portfolios. Music Sentiment is the contemporaneous weekly change of the stream weighted average valence on the Spotify Top 200 list in Sweden. Controls include: The past week return of the OMXSPI Index, the Swedish Statistical Central Bureau's Macroeconomic Index, the value of the V2TX Index, measuring the implied volatitliy of the EURO STOXX 50 Index, the value of the European Economic Policy Uncertainty Index and the average daily change in deseasonalized cloud cover in Sweden. The table shows the standard errors in parentheses. Constants are not reported.

	Dependent variable: Portfolio Returns		
	(1)	(2)	(3)
Music Sentiment	0.188*	0.204*	0.292**
	(0.107)	(0.108)	(0.119)
Controls	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Observations	401	392	401
R^2	0.130	0.121	0.143
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 10 presents the estimation results of Eq. (6)-(8), grouped by stock beta. Column 1 presents the Small Group regression, Column 2 the Medium Group regression, and Column 3 the Large Group regression. Our findings reveal that music sentiment is positively correlated with equally weighted portfolio returns across all size groups, though the relationship is statistically significant only for the large group at the 10% level. Examining the table from left to right, we observe a gradual increase in the estimated coefficient for music sentiment, suggesting that stocks with higher betas are relatively more sentiment-prone. Namely, for the large group, a one standard deviation increase in music sentiment is associated with a 0.93% higher portfolio return during the corresponding week. For the medium and small group portfolios, the same increase corresponds to a 0.63% and 0.39% higher return, respectively.

This finding aligns with previous research suggesting that stocks with high betas are more sentiment-prone. However, given the lack of statistical significance, our findings do not provide adequate support for this relationship.

Similar to previous models, we conduct a two-sided Wald test to determine whether the music sentiment estimate for the large group portfolio is significantly larger than that of the small group. The test shows no statistical significance, indicating that the observed differences in sentiment sensitivity between the groups are not statistically meaningful. Consequently, our findings provide only weak support for previous research findings.

Table 10: OLS Linear Regression: Cross Sectional Returns - MARKET BETA. Column 1 show the estimation results of Eq.(6), column 2 show the results of Eq.(7) and column 3 the result of Eq.(8), grouped by market beta. Dependent variable is weekly return of the group portfolios. Music Sentiment is the contemporaneous weekly change of the stream weighted average valence on the Spotify Top 200 list in Sweden. Controls include: The past week return of the OMXSPI Index, the Swedish Statistical Central Bureau's Macroeconomic Index, the value of the V2TX Index, measuring the implied volatitliy of the EURO STOXX 50 Index, the value of the European Economic Policy Uncertainty Index and the average daily change in deseasonalized cloud cover in Sweden. The table shows the standard errors in parentheses. Constants are not reported.

	Dependent variable: Portfolio Returns		
	(1)	(2)	(3)
Music Sentiment	0.106	0.169	0.251*
	(0.081)	(0.104)	(0.134)
Controls	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
Observations	401	401	401
R^2	0.103	0.128	0.133
Note:			*p<0.1; **p<0.05; ***p<0.01

5 Conclusion

This study examines the relationship between music sentiment and stock returns in Sweden, using stream-weighted average valence (music sentiment) as a novel sentiment proxy. The findings underscore a statistically significant and positive link between music sentiment and same-week stock returns, suggesting sentiment's influence on market behavior. Interestingly, the research reveals a price correction pattern, where sentiment-induced returns reverse in the subsequent week. This aligns with prior literature on sentiment's transient market impact. While the results are statistically significant, they should be interpreted with caution as they do not fully substantiate a conclusive relationship due to limited statistical reliability.

The analysis extends to firm-level returns and cross-sectional variations, confirming that music sentiment impacts a broad spectrum of industries and stock profiles. While the effects are evident across industries, high beta and financially distressed stocks exhibit greater sensitivity to sentiment changes. Nevertheless, these findings have varying levels of significance and lack statistical robustness and should be analyzed with care.

The study enhances the literature by focusing on Sweden, a market with significant retail investor participation and high Spotify usage. Despite limitations, such as sample size and data constraints, the results substantiate the role of music sentiment as a relevant behavioural finance measure. Future research could explore sentiment dynamics in other cultural or market contexts to deepen understanding.

6 Discussion

This study's findings underscore the potential of music sentiment to predict stock returns in Sweden. However, these insights should be interpreted with caution due to several methodological and contextual factors.

Firstly, while music sentiment offers a novel and high-frequency measure of sentiment, its applicability might be limited by data bias. Spotify usage in Sweden is high but may not represent the sentiment of the entire investor population, particularly institutional investors or older demographics who may not engage with the platform as extensively. Future studies could explore additional proxies for sentiment to validate and complement these results.

Secondly, the observed impact of music sentiment on stock returns in Sweden supports previous findings in Edmans et al. (2021), Fernandez-Perez (2020) and Can et al. (2023) who document its effect on stock returns. However, the statistical weakness in some of our results, raises questions about the robustness of these findings. For instance, some of our results have high standard errors, varying levels of significance and showed inconsistencies in robustness checks. Future research could employ larger datasets or more refined econometric techniques to reduce noise and clarify these relationships.

Furthermore, while the results are consistent with global studies such as Edmans et al. (2021), Sweden's unique characteristics, such as high retail investor participation and Spotify penetration, may limit the generalizability of these findings. Exploring the same relationships in markets with different cultural and economic contexts could provide valuable insights into whether the observed sentiment effects are universal or context-dependent.

Finally, the time frame of this study, spanning 2017 to 2024, captures significant macroeconomic and geopolitical events, including the COVID-19 pandemic and geopolitical tensions. These events might have amplified or muted sentiment-driven behaviors. Future research could examine whether sentiment effects vary during periods of economic stability versus crisis, further enriching our understanding of sentiment dynamics.

This study contributes to the behavioural finance literature by demonstrating the relevance of music sentiment in financial markets, while also paving the way for future research to further explore and refine these findings across diverse contexts and methodologies.

Appendix

Table 11: Music Sentiment and OMXSPI Returns with Year-Month Fixed Effects. This table shows the estimation results of Eq.(2) in column 1 and (3) in column 2, but with year-month fixed effects for robustness check. The table shows the standard errors in parentheses. Constants are not reported.

	Dependent variable: OMXSPI Returns	
	(1)	(2)
Music Sentiment	0.248^{**}	
	(0.109)	
Music Sentiment (t-1)		-0.186
		(0.115)
Controls	Yes	Yes
Fixed Effects	Y-M	Y-M
Observations	401	400
R^2	0.377	0.372
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 12: Music Sentiment and OMXSPI Returns: Robustness Check. This table shows the estimation results of Eq.(2) in column 1 and (3) in column 2, but with music sentiment and lagged music sentiment included in the same model. The table shows the standard errors in parentheses. Constants are not reported.

	Dependent variable: OMXSPI Returns	
	(1)	(2)
Music Sentiment	0.212^{*}	0.162
	(0.112)	(0.111)
Music Sentiment (t-1)	-0.295^{***}	-0.291^{***}
	(0.113)	(0.111)
Controls	No	Yes
Month Fixed effects	Yes	Yes
Observations	400	400
R^2	0.055	0.121
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 13: Panel Regression: Company Returns and Music Sentiment with Year-Month Fixed Effects. This table shows the estimation results of Eq.(4) in column 1 and (5) in column 2, but with year-month fixed effects for robustness check. The table shows the standard errors in parentheses. Constants are not reported.

	Dependent variable: Company Returns	
	(1)	(2)
Music Sentiment	0.265^{***}	
	(0.014)	
Music Sentiment (t-1)		-0.149^{***}
		(0.014)
Controls	Yes	Yes
Fixed effects	Firm,Y-M	Firm, Y-M
Observations	138,306	137,839
R^2	0.02	0.018
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 14: Music Sentiment and Company Returns: Robustness Check. This table shows the estimation results of Eq.(4) in column 1 and (5) in column 2, but with music sentiment and lagged music sentiment included in the same model. The table shows the standard errors in parentheses. Constants are not reported

	Dependent variable: Company Returns	
	(1)	(2)
Music Sentiment	0.200^{***}	0.152^{***}
	(0.013)	(0.013)
Music Sentiment (t-1)	-0.265^{***}	-0.281^{***}
	(0.013)	(0.014)
Controls	No	Yes
Month Fixed Effects	Yes	Yes
Observations	137,839	137,839
R^2	0.003	0.014
Note:		*p<0.1; **p<0.05; ***p<0.01

Figure 3: Summary of two sided Wald-test to test if the estimate for the large group portfolio returns is significantly larger than the estimate of the small group. See tables 6 to 9.

Wald Test Statistic (EXTF): 0.4272825

P-value (EXTF): 0.5133254

Wald Test Statistic (BETA): 0.8595143

P-value (BETA): 0.3538747

Wald Test Statistic (DA): 0.7413438

P-value (DA): 0.3892308

Wald Test Statistic (BTM): 0.3635197

P-value (BTM): 0.5465579

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7 AI Transparency Statement

In order to correct grammar, spelling and find synonyms to avoid repetitive use of certain words, we have utilized ChatGPT 4o. Furthermore, it helped us in our coding process with troubleshooting syntax errors. For this purpose, some parts of our paper and corresponding code was uploaded to the web-based tool.