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Music sentiment and the cross-section of stock returns in the US

Shiqi Chen, Yiwei Wang, Huiyi Zhang, Jie Zhou

School of Economics and Management, Nanjing University of Science and Technology, Nanjing 210094, China

Abstract. This paper examines the role of music sentiment, which endogenously measures investor sentiment, in the cross-sectional pricing of individual stocks in the US. We estimate individual stocks' exposure to country-level music sentiment and find that, following periods of low music sentiment, stocks with the highest sentiment beta significantly outperform those with the lowest sentiment beta on a daily basis in the future on a risk-adjusted basis. However, this return spread is not significant following high-sentiment periods, demonstrating an asymmetric pricing effect. This finding is consistent with the argument that overpricing following high-sentiment periods is more prevalent than underpricing following low-sentiment periods because of short-sale constraints.

Keywords: Music sentiment; Asset pricing; Asymmetry; Cross-sectional stock returns.

1. Introduction

The question of how market sentiment affects asset prices has drawn considerable attention over the past few decades. While numerous studies have shed light on how aggregate market sentiment impacts time-series asset returns (see, e.g., Alex Edmans et al., 2022; K Obaid et al., 2022), less attention has been paid to how sentiment explains the cross-section of expected stock returns. Until now, only a few papers have empirically focused on the pricing ability of sentiment beta, which measures the sensitivity of stock returns to fluctuations in sentiment risk. Glushkov (2006) finds that the relation between sentiment beta and stock returns has an inverse U-shape; that is, stocks with extreme values of sentiment beta earn lower future returns relative to those with near-zero sentiment beta. In contrast, Ho and Hung (2012) report a U-shape pattern in stock returns across portfolios sorted by sentiment beta. Shen, Yu, and Zhao (2017) show that sentiment beta is positively (negatively) priced following low (high) sentiment periods. Liang (2018) finds a positive relation between sentiment beta and expected stock returns. In addition, Jacoby. et al (2024) find that high-sentiment beta stocks obtain higher cross-sectional returns only following low-sentiment months, and there is no relation between sentiment beta and returns following medium-sentiment and high-sentiment months. In short, how sentiment exposure affects expected stock returns remains an open question, with existing studies providing mixed and sometimes contradictory evidence on how sentiment beta is priced. The question of the sign of the sentiment risk premium remains open, and there is no consensus.

In this paper, we adopt an alternative approach to capture individuals' mood. To do so, we draw on psychological literature, which shows that music choices reveal mood states. Greenberg et al. (2016) show that music preferences are related to personality traits (such as extroversion, depression, and anxiety). In addition, Hunter et al. (2011) examine emotional responses to music after emotional induction and find that listeners in a sad mood are unable to show the typical preference for happy music; instead, they perceive more sadness in the music. In particular, Mehr et al. (2019) find that music not only has universality but also that similar music is used in similar situations around the world. This further indicates that the measurement of music sentiment is applicable globally and that music can capture emotions that other methods cannot measure.

Our paper makes several marginal contributions. First, we adopt the music sentiment proposed by Edmans et al. (2022) as a market-level investor sentiment indicator, which is a novel and efficient measure, differing from previous studies that exploit traditional indices (see, e.g., Baker and Wurgler, 2006; Da et al., 2015) or other textual analysis methods. Second, we empirically explore the direct pricing ability of daily market-wide sentiment beta in the cross-section of US stock returns from a relatively high-frequency perspective, differing from the traditional asset pricing paradigm that typically adopts monthly frequency, and show that sentiment can affect cross-sectional returns. Our paper thus enriches studies on the important role of sentiment in asset pricing (Xie et al., 2024). Third, to the best of our knowledge, we are the first to examine the pricing ability of daily music sentiment beta following specified (low or high) sentiment periods in the US, demonstrating an asymmetric pricing effect.

2. Data and key variables

2.1. Sentiment beta

Stock market data are extracted from the Center for Research in Security Prices (CRSP), and accounting data are obtained from Compustat. We use a sample of S&P 500 firms over the period from 2017 to 2023. Stocks in the financial and utility sectors (CRSP SIC codes 6000-6999 and 4000-4999) are excluded. We use daily common risk factors, such as market (MKT), size (SMB), value (HML), profitability (RMW), and investment (CMA), from Kenneth French's online data library.

Music sentiment beta is calculated based on the music sentiment we constructed, following Alex Edmans et al (2022). We construct a stream-weighted average valence (henceforth, SWAV) across the top 200 songs for each day in the US from 2017 to 2023. (Spotify has an algorithm that classifies a song's valence, which measures the musical positiveness conveyed by a song and ranges from 0 to 1. Songs with high valence sound more positive.)

Numerous studies explore the level of market sentiment as an interpretive or conditional factor in asset pricing and anomaly studies (Baker and Wurgler, 2006; Stambaugh, Yu, and Yuan, 2012, 2015). On the contrary, our study sheds light on the risk exposure to the fluctuations in market sentiment. Our measure of music sentiment is persistent, with a highly positive first-order autocorrelation coefficient and a unit root, whereas its first difference is stationary. Hence, we use the change in SWAV to measure fluctuations in music sentiment, which reflect market-level investor sentiment.

For each stock and each month from January 2017, following previous studies (Chen, et al., 2021; Zhang, et al., 2023; Zhang, et al., 2024), we conduct the following time-series regression with a 60-day rolling window, requiring at least 24 observations, and we also control for the market excess return to isolate the information contained in the sentiment index that is correlated with market returns, in order to reduce endogeneity in the model. Hence, we use the change in SWAV to measure fluctuations in music sentiment, which reflect market-level investor sentiment.

$$r_{i,t} = \alpha + \beta_{i,0}\Delta SWAV_t + \beta_{i,1}\Delta SWAV_{t-1} + \beta_{i,CAPM} r_{m,t} + \varepsilon_{i,t}$$

$$\beta_{i,music\_senti} = \beta_{i,0} + \beta_{i,1}$$

2.2. Other variables

We also employ several other variables. These serve as controls to demonstrate that the predictive role of sentiment beta is not influenced by these common factors, ensuring that sentiment beta is an independent predictor. Following Chen et al. (2023), we use the natural logarithm of the previous month's closing price multiplied by the total number of shares outstanding to construct firm size (SIZE). Following Fama and French (1992), book-to-market ratio (BM) equals the natural logarithm of the book value of equity divided by the market value of tradable shares. Following Amihud (2002), we use the ratio of the daily absolute stock return to the daily trading volume averaged in each month to construct illiquidity (ILLIQ). Using the company's net income divided by book equity, we construct return on equity (ROE). Following Fama and French (2015), we use the annual asset growth rate of a firm to measure investment.

We match the monthly information for BM and ROE from month t-1 to daily returns in month t (the CRSP/Compustat Merged database provides a monthly time series of financial ratios per company). We match the quarterly information for investment from quarter t-1 to daily returns in quarter t.

3. Empirical results

3.1. Average and risk-adjusted returns of sentiment beta decile portfolios

We use data from January 3, 2017, to March 29, 2017, as the initial music sentiment beta construction period. Starting from March 30, 2017, we sort all S&P 500 stocks according to their music sentiment beta value from the previous day and divide them into ten groups. We construct a long-short portfolio by going long on stocks in decile group 10 and short on stocks in decile group 1, based on music sentiment beta.

To explore the asymmetric pricing effect conditional on music sentiment beta following high- versus low-sentiment periods, we use 30%/40%/30% breakpoints of the daily music sentiment variable (the change in SWAV) to define high, medium, or low music sentiment days.

Table 1. Univariate sorts by music sentiment beta following the low-sentiment periods

Decile	low	2	3	4	5	6	7	8	9	High	High-low
Return	1.205	0.606	0.491	0.572	0.692	0.569	0.962	1.051	1.426	3.915	2.710
	(1.323)	(0.906)	(0.748)	(1.111)	(1.338)	(1.080)	(1.789)	(1.787)	(1.993)	(3.976)	(2.391)
α_{CAPM}	0.665	0.111	0.013	0.206	0.372	0.281	0.579	0.628	1.037	3.562	2.897
	(0.845)	(0.294)	(0.047)	(1.072)	(2.231)	(1.636)	(3.441)	(2.676)	(2.623)	(4.108)	(2.442)
α_{FF3}	0.589	0.084	0.014	0.209	0.383	0.293	0.584	0.617	1.197	3.467	2.878
	(0.925)	(0.230)	(0.047)	(1.070)	(2.276)	(1.691)	(3.579)	(2.726)	(2.775)	(4.297)	(2.433)
α_{FF5}	0.762	0.080	0.032	0.150	0.395	0.258	0.592	0.673	1.054	3.597	2.835
	(1.169)	(0.215)	(0.110)	(0.792)	(2.147)	(1.504)	(3.610)	(2.982)	(3.061)	(4.859)	(2.432)

Note: This table reports daily average excess returns, alphas (in percent), and their Newey-West (1986) adjusted t-statistics (in parentheses) for sentiment beta decile portfolios following low-sentiment periods. All portfolios are rebalanced daily and value-weighted.

From the perspective of returns following low-sentiment periods, Table 1 clearly shows that when we regress the returns of this sentiment beta long-short portfolio on the factors of each model, the resulting alpha, meaning the unexplained return component after accounting for the model's factors—are all statistically significant. For instance, the CAPM alpha stands at 2.897% with a t-statistic of 2.442, the Fama-French three-factor alpha is 2.878% (with a t-statistic of 2.433), and the five-factor alpha is 2.835% (with a t-statistic of 2.432). More importantly, these alphas remain stable in magnitude even as we add more factors to the model, which means the return premium from music sentiment beta cannot be attributed to the market risk, size, value, profitability, or investment risks captured by the three models, and this confirms that music sentiment beta represents a unique risk dimension that traditional factor models fail to explain.

Table 2. Univariate sorts by music sentiment beta following the high-sentiment periods

Decile	low	2	3	4	5	6	7	8	9	High	High-low
Return	2.532	1.761	1.161	1.053	0.863	1.007	1.335	1.345	1.143	1.234	-1.298
	(2.515)	(2.103)	(1.775)	(1.804)	(1.606)	(1.838)	(2.360)	(2.228)	(1.599)	(1.304)	(-1.215)
α_{CAPM}	1.695	0.895	0.614	0.343	0.243	0.459	0.614	0.675	0.398	0.589	-1.105
	(2.488)	(1.741)	(2.007)	(1.444)	(1.584)	(2.684)	(3.476)	(2.244)	(1.038)	(0.898)	(-1.133)
α_{FF3}	1.734	0.866	0.560	0.311	0.183	0.419	0.575	0.645	0.371	0.584	-1.150
	(2.654)	(1.776)	(1.857)	(1.326)	(1.082)	(2.430)	(3.364)	(2.165)	(0.986)	(0.923)	(-1.124)
α_{FF5}	1.780	0.795	0.505	0.279	0.168	0.383	0.602	0.734	0.501	0.511	-1.269
	(2.783)	(1.732)	(1.709)	(1.185)	(0.986)	(2.299)	(3.569)	(2.542)	(1.366)	(1.515)	(-1.108)

Note: This table reports daily average excess returns, alphas (in percent), and their Newey-West (1986) adjusted t-statistics (in parentheses) for sentiment beta decile portfolios following high-sentiment periods. All portfolios are rebalanced daily and value-weighted.

Table 2 shows that, following high-sentiment periods, the long-short portfolios do not achieve significant alphas or abnormal returns not explained by the common factor models. In addition, in an unreported table, we examine abnormal returns over the full sample period and do not find a significant alpha, likewise when controlling for the common factor models.

3.2. Double sorts on sentiment beta and related variables

Firm size is correlated with sentiment change exposure: Smaller firms are more susceptible to investor sentiment. To explore whether music sentiment beta has incremental information beyond firm size, we first rank the previous day's market value into quintiles and, within each quintile, sort into quintiles based on music sentiment beta.

Table 3. Bivariate sorts by music sentiment beta and size following low-sentiment periods

Decile	Low	2	3	4	High	High-Low
Return	0.105	0.218	0.284	0.391	0.652	0.547
	(0.211)	(0.543)	(0.812)	(1.234)	(2.145)	(2.891)
α_{CAPM}	0.088	0.194	0.267	0.378	0.635	0.547
	(0.178)	(0.485)	(0.765)	(1.195)	(2.101)	(2.905)
α_{FF3}	0.075	0.181	0.251	0.361	0.618	0.543
	(0.152)	(0.453)	(0.722)	(1.147)	(2.056)	(2.888)
α_{FF5}	0.072	0.177	0.247	0.355	0.609	0.537
	(0.146)	(0.443)	(0.711)	(1.131)	(2.028)	(2.864)

Note: This table reports daily average excess returns, alphas (in percent), and their Newey-West (1986) adjusted t-statistics (in parentheses) for double-sorted portfolios on music sentiment beta and size following low-sentiment periods. All portfolios are equal-weighted and rebalanced daily.

Table 3 shows a significant increase in excess returns as music sentiment beta increases after double sorting. In addition, we calculate risk-adjusted returns and obtain significant alphas following low-sentiment periods, indicating that factor models do not explain double-sorted portfolios well. Likewise, the return spread is not significant following high-sentiment periods when using double sorting, according to Table 4.

Table 4. Bivariate sorts by music sentiment beta and size following high-sentiment periods

Decile	Low	2	3	4	High	High-Low
Return	0.321	0.285	0.254	0.230	0.198	-0.123
	(1.112)	(1.045)	(0.987)	(0.892)	(0.754)	(-0.645)
α_{CAPM}	0.302	0.271	0.243	0.221	0.187	-0.115
	(1.056)	(1.002)	(0.951)	(0.862)	(0.718)	(-0.607)
α_{FF3}	0.295	0.264	0.238	0.215	0.179	-0.116
	(1.034)	(0.978)	(0.933)	(0.841)	(0.689)	(-0.612)
α_{FF5}	0.291	0.261	0.235	0.212	0.175	-0.116
	(1.021)	(0.968)	(0.923)	(0.830)	(0.674)	(-0.614)

Note: This table reports daily average excess returns, alphas (in percent), and their Newey and West (1986) adjusted t-statistics (in parentheses) of double-sort portfolios based on music sentiment beta and size following high-sentiment periods. All portfolios are equal-weighted and rebalanced at a daily frequency.

3.3. Fama-MacBeth regressions

The foregoing analysis demonstrates the importance of music sentiment beta as a cross-sectional determinant of future returns following low-sentiment periods. However, portfolio-level analysis has drawbacks, such as the difficulty of controlling for multiple factors simultaneously. Therefore, we use Fama-MacBeth (FM) regressions to explore whether the music sentiment beta premium in the US stock market is affected by other important variables following low-sentiment periods, including β_{MKT} (market beta), SIZE (log firm size), BM (log book-to-market ratio), ILLIQ, ROE, Investment, and MOM (momentum). The daily cross-sectional regression is expressed as

$$r_{i,t+1} = \gamma_t + \gamma_t^{music\_senti}\beta_{i,t,music\_senti} + \gamma_t^x X_{i,t} + \varepsilon_{i,t+1},$$

Where $r_{i,t+1}$ is the excess return of stock *i* in day t+1 and $\beta_{i,t,music\_senti}$ is the music sentiment beta of stock *i* in day *t*. $X_{i,t}$ represents an empty set or a collection of control variables (β_{mkt}, SIZE, BM, ILLIQ, ROE, Investment, MOM).

These results underscore the robustness of the music sentiment beta premium: even when controlling for a set of core asset pricing variables (including market beta, firm size, book-to-market ratio, illiquidity, profitability, investment, and momentum—factors long proven to drive cross-sectional returns), the premium remains statistically significant.

Quantitatively, Table 5 shows the music sentiment beta coefficient barely fluctuates (staying 0.133–0.138) with t-statistics above 2.5 across all regression specs, confirming no confounding effects from traditional factors. Meanwhile, the adjusted R^2 rises only slightly: from 0.023 (only music sentiment beta) to 0.083 (all controls). This tiny increase means common control variables explain just a small fraction of return variation, while music sentiment beta captures a unique, sentiment-driven risk premium that can't be substituted by conventional pricing factors.

Table 5. Fama-Macbeth regressions

DepVar:One-day-ahead excess returns					
β_{music_senti}	0.138 (2.577)	0.134 (2.520)	0.134 (2.569)	0.135 (2.531)	0.133 (2.542)
β_{CAPM}		0.016 (0.364)	0.011 (0.248)	0.012 (0.264)	0.010 (0.273)
SIZE			-0.096 (-4.423)	-0.101 (-6.096)	-0.100 (-5.013)
BM			0.044 (3.012)	0.050 (3.697)	0.050 (3.547)
ILLIQ				0.013 (1.469)	0.011 (1.259)
ROE				-0.018 (-1.250)	-0.017 (-1.142)
Investment				0.014 (1.912)	0.012 (1.813)
MOM					-0.006 (-0.197)
Adj.R^2	0.023	0.059	0.071	0.081	0.083

Note: This table reports the results of FM regressions of one-day-ahead stock excess returns on music sentiment beta, controlling for other variables, following low-sentiment periods. All independent variables are minorized at the 1st and 99th percentiles and then normalized to have a zero mean and standard deviation of one.

4. Explanation

According to previous studies (e.g., DeLong et al., 1990; Lee et al., 1991), fluctuations in sentiment itself pose a risk to arbitrageurs, and Lee, Jiang, and Indro (2002) suggest that sentiment is a systematic risk in the stock market. Kozak, Nagel, and Santosh (2018) show that sentiment risk can be priced when there are common components in the demand for sentiment-driven assets, because arbitrageurs must take risks to counter these positions. This demonstrates that a change in sentiment serves as a state variable proxying for variations in investment opportunities in the conditional intertemporal capital asset pricing model (ICAPM) framework. Thus, it is well-founded to directly employ sentiment risk exposure as a pricing factor, grounded in sound economic theory. In the following section, we focus on the potential explanation for the sign of the sentiment risk premium in our empirical results and the asymmetric pricing ability across different sentiment periods.

Based on psychological literature showing that individuals reflect their mood in their music choices, music sentiment serves as an endogenous and direct proxy for investor sentiment in the US (Edmans et al., 2022), representing country-level and market-level investor sentiment. In the dynamic model of Kozak et al. (2018), time-varying sentiment gives rise to time-varying hedging demand by arbitrageurs. As a result, time-varying sentiment can create a state variable that proxies for shifts in the investment opportunity set, with expected returns reflecting this state-variable risk.

Assets with negative (low) music sentiment exposures provide higher returns when investors face poor investment opportunities relative to assets with positive sentiment exposures, because a decrease in sentiment generates higher returns for assets with negative sentiment exposure. Hence, when music sentiment decreases and investment opportunities decline, the higher returns from these assets serve as a hedge for investors. Consequently, investors are willing to accept lower expected returns from these stocks with negative (low) music sentiment exposure. Meanwhile, assets that positively covary with music sentiment carry a positive risk premium because investors require additional compensation to hold riskier assets (high music sentiment beta stocks). In addition, following low-sentiment periods, sentiment-driven investors are collectively pessimistic but constrained by short-sale impediments, whereas rational investors face no such limits in correcting underpricing. Thus, underpricing is less likely following low-sentiment periods, and prices more closely reflect fundamental values, making the risk-return tradeoff more prominent in these periods (Shen, Yu, and Zhao, 2017). In such an environment, the compensation for bearing sentiment risk becomes clearer. Accordingly, we find that the positive relationship between sentiment beta and expected returns holds following low-sentiment periods but not following high-sentiment periods, demonstrating an asymmetry in the sentiment beta effect conditional on music sentiment reflecting endogenous market-level investor sentiment. This is consistent with the presence of short-sale constraints (Nagel, 2005).

5. Conclusion

To test whether music sentiment is priced in the cross-section, we regress daily excess stock returns on music sentiment to estimate daily individual stock loadings on music sentiment, which we term sentiment betas. We sort stocks into deciles and quintiles based on their sentiment betas and find that stocks with high (low) loadings on market-level sentiment generate significantly higher (lower) returns following low-sentiment periods. However, this return spread is not significant following high-sentiment periods, demonstrating asymmetry and supporting the argument that overpricing following high-sentiment periods is more prevalent than underpricing following low-sentiment periods due to short-sale constraints.

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