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Popular Music, Sentiment, and Noise Trading

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Abstract

We construct a sentiment indicator as the first principal component of thirteen emotion metrics derived from the lyrics and composition of music-chart singles. This indicator performs well, dominating the Michigan Index of Consumer Sentiment and bettering the Baker-Wurgler index in long-horizon regression tests as well as in out-of-sample forecasting tests. The music-sentiment indicator captures both signal and noise. The part associated with fundamentals predicts more distant market returns positively. The second part is orthogonal to fundamentals, and predicts one-month-ahead market returns negatively. This is evidence of noise trading explained by the emotive content of popular music.

Keywords: investor sentiment, stock-return predictability, big data, textual analysis, natural language processing, popular music, noise trading, behavioral finance

JEL classification: G12, G17, C55

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1 Introduction

Big data offers the prospect of direct, fine-grained, and timely economic indicators. We exploit big data in this paper to capture market sentiment. Unlike surveys or indirect indicators of sentiment, our popular-music big-data approach captures more directly emotions being experienced economy-wide, and the relative frequencies thereof.

Emotional responses and observable related behaviors trigger similar emotions and behaviors in others: they are contagious. Recent work has shown that emotional contagion can also occur at massive scale through indirect observation of others' emotional experiences as related in social-media posts (Kramer et al. 2014). Music in particular serves as a medium for capturing, reproducing, and communicating emotions. Music composition encodes universal emotional cues, while lyrics encode culturally specific emotional cues. Hence music tracks are carriers of emotional contagion (Lundqvist et al. 2009). *Popular* music — which by construction is heard frequently, by many people — is a population-spanning carrier of emotional contagion.

We develop a popular-music-based sentiment indicator and evaluate its performance. Our performance-evaluation strategy employs both time-series and cross-sectional specifications, and includes well-tested sentiment-indicator performance benchmarks: the Michigan Index of Consumer Sentiment ($MICS$), and the Baker and Wurgler (2006, 2007) First Principal Component Sentiment index ($SFPC$-BW).

Our popular-music-based sentiment indicator exploits natural-language processing and composition-attributes metrics for tracks appearing in the Billboard Hot 100 list (in the US) and the Official Charts Company list (in the UK). These music-industry charts document the frequency with which individual tracks are played in specific market segments. The universal emotional attributes of these tracks are captured in five feature-based indicators available from the Spotify Developer API: danceability, energy, tempo, loudness, and valence. The culturally specific component is extracted from the music-chart tracks by mapping their lyrics onto the Word-Emotion Association Lexicon (EMOLEX), yielding eight emotive-word indicators. Initial analyses have shown these indicators to be promising sources of sentiment information (Sabouni, 2018).

From these thirteen indicators we aim to extract a reliable 'composite' indicator with which we may rigorously test whether music-based sentiment is predictive of S&P500 market returns, and how this predictive power measures up against the sentiment-indicator performance benchmarks, $MICS$ and $SFPC\text{-}BW$.

We refer to the new composite indicator as the First Principal Component Music Sentiment indicator ($SFPC\text{-}M$). It displays predictive power comparable to $SFPC\text{-}BW$ — and indeed dominant with respect to $MICS$ — in long-horizon regressions which include controls for macroeconomic fundamentals. Increases in music sentiment uncorrelated with fundamentals predict decreases in one-month-ahead returns. This is consistent with the notion that positive music sentiment motivates optimistic stock purchases, driving stock prices up in the short run, which then revert back to fundamentals when the noise-shock of positive music sentiment subsides. In other words, the negative one-month-ahead market reaction is consistent with the hypothesis that *noise traders* respond to popular-music sentiment. Further empirical tests show that the effect of music sentiment is greatest during recession periods. The cross-section of stock returns reveals that small firms, high-volatility firms, unprofitable firms, non-dividend-paying firms, and extreme growth firms are particularly sensitive to music sentiment. As in the time-series domain, cross-sectional results show that for firms that are sensitive to sentiment, positive-sentiment shocks result in negative subsequent returns. But the horizon over which prices revert to fundamentals differs depending on the speed at which the 'information-arrival clock' runs for the financial characteristic in question. For some financial-characteristic classes, the reversion initially overshoots. Price re-discovery following a positive sentiment shock is neither automatic nor direct. Finally, in out-of-sample tests, $SFPC\text{-}M$ shows at least as much predictive power as $SFPC\text{-}BW$ in rolling-and-recalibrating models, and superior predictive power in rolling-window models. In both within- and out-of-sample tests, the music-sentiment indicator retains independent predictive power even after controlling for $SFPC\text{-}BW$; the most powerful within- and out-of-sample models feature *both* $SFPC\text{-}M$ and $SFPC\text{-}BW$. In other words, the present big-data-based music-sentiment indicator captures new information not available in conventional sentiment indicators, and by virtue of this fact is best used in combination with conventional indicators.

Our approach shares some commonalities with Da, Engelberg, and Gao's (2015) Financial and Economic Attitudes Revealed by Search (FEARS) index. Like FEARS, our music-sentiment indicator captures *revealed* information rather than consciously formulated responses to questions. An individual may choose to Google-search for "recession" either because of personal concerns and beliefs or because of an interest in learning about others' beliefs and concerns (or possibly both). Similarly an individual may choose to listen to a particular music track either because it aligns with their mood and personal preferences or because of a desire to share the experience with other people (or possibly both). There are also differences. The FEARS index can be updated on a daily basis, whereas music sentiment is restricted by the weekly music-chart production cycle. Also, although the threshold of initiative and effort required to formulate and execute a Google search is low in absolute terms, it may be higher in relative terms than the initiative and effort required to listen to Spotify's personalized recommended-music list, to listen to one's own list on 'shuffle', to skip over tracks that one doesn't want to listen to at the moment, to listen to music on one's favorite radio station, or to switch over to listening to one's second-most-favorite radio station. Moreover, by construction FEARS gauges changes in the level of negative sentiment, whereas the music-sentiment indicator captures both positive- and negative-valence emotions. Hence the study of music sentiment is not *a priori* rendered redundant by FEARS.[1]

[1]Inclusion of FEARS as an additional benchmark indicator is deferred to future work, for reasons outlined below on page 11, footnote 9.

2 Music sentiment

2.1 Composite music-sentiment indicator

We start with thirteen monthly pop-music indicators originally studied by Sabouni (2018).[2] These indicators are extracted from weekly charts of the most popular tracks — the Billboard Hot 100 list in the US[3] and the Official Charts Company in the UK[4] — during the period starting from January 2000, running through to the end of 2016. By construction these popular music charts combine radio-play statistics, which are influenced by the choices and marketing efforts of record labels, with sales and streaming statistics, which reflect consumer choices made in light of a large background information set including radio play and other peoples' listening choices.

The thirteen music-sentiment indicators fall into two categories.

Five are feature-based indicators obtained from the Spotify Developer API, which capture different attributes of a listed music track: its danceability, energy, tempo, loudness, and valence.[5] These indicators capture culturally universal emotive features. Online music-streaming services use these and related attributes to categorize songs and to recommend new music to individual users based on similarity with their music-streaming history. Aggregate indicators are obtained as the average across tracks of individual feature values.

The remaining eight are culturally specific emotive-word indicators, obtained by cross-referencing lyrics with the Word-Emotion Association lexicon from the National Resource Council of Canada (EmoLex). EmoLex maps a large set of English words onto eight basic emotions: joy, sadness, anger, fear, trust, disgust, anticipation and surprise. Plutchik (2001) argues that the eight basic emotions can be viewed as four complementary pairs (joy-sadness, anger-fear, anticipation-surprise and trust-disgust), and that more complex human emotions are constructed from combinations of the eight basic emotions. The basic-emotion indicators are obtained as the per-track average of

[2]We thank Hisam Sabouni for sharing his data.

[3]radio play, retail and digital sales, and online streaming in the US

[4]retail and digital sales, and online streaming in the UK

[5]'Valence' denotes the musical positiveness of a track.

the number of word occurrences that are associated with that basic emotion, where on average 70 of the month's 100 tracks are successfully matched (Sabouni, 2018).

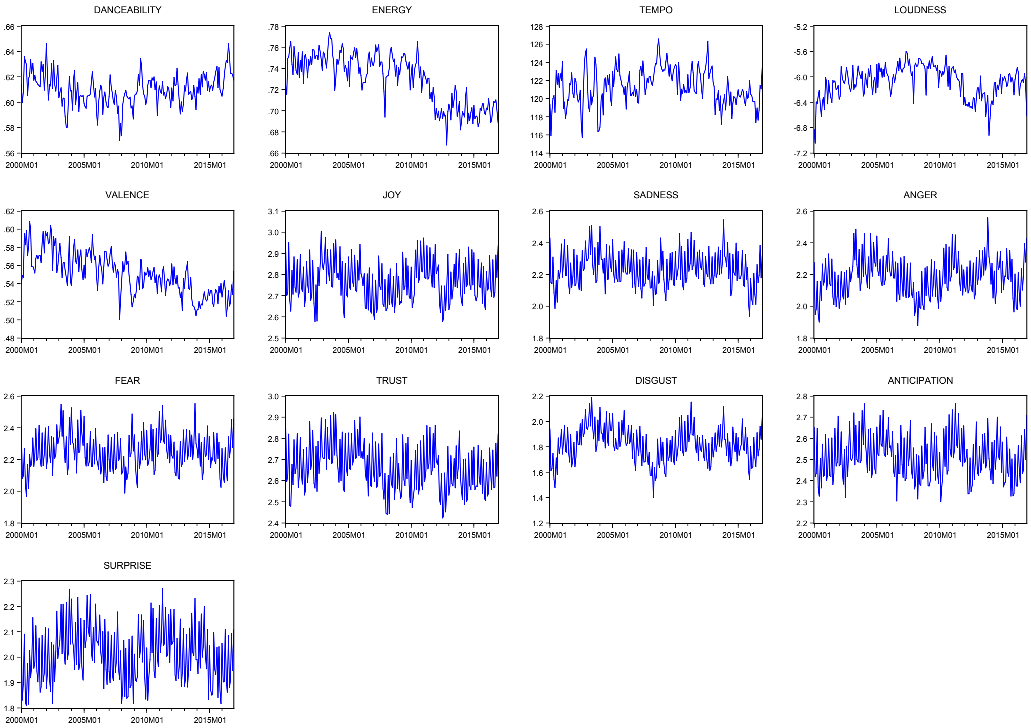
Time-series plots of the thirteen raw indicators are displayed in Panel A of Figure 1. For each pair of indicators, Table 1 reports the correlation coefficient, t-statistic, and the associated p-value. Several regularities are apparent.

First, the five feature-based indicators are intercorrelated. For instance, danceability is significantly correlated with tempo and valence; energy is significantly correlated with tempo, loudness and valence; tempo with danceability, energy and loudness; loudness with energy, tempo and valence; valence to danceability, energy and loudness.

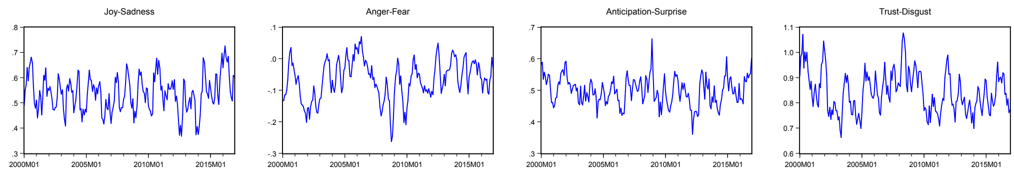
Second, correlations between feature-based indicators as well as between feature-based and emotive-word indicators are small in magnitude, typically $|\rho| < 0.3$, except for that between energy and loudness/valence. This correlation structure suggests that different information is captured by different indicators, leading to low, if significant correlations. These correlations suggest retaining the whole set of indicators for joint analysis.

Third, the eight emotive-word indicators are all strongly and significantly intercorrelated ($\rho > 0.747$). Hence the raw emotive-word indicators may not be individually informative enough, nor sufficiently independent to avoid multicollinearity, in further analysis. Consequently we take the complementary pairs — joy–sadness, anger–fear, anticipation–surprise and trust–disgust — and we form four new indicators as the arithmetic within-pair difference. We also posit that these difference indicators may better capture the relative strength of competing basic emotions reflected in consumers' music-listening choices. The four emotive word-pair differences are presented in Panel B of Figure 1.

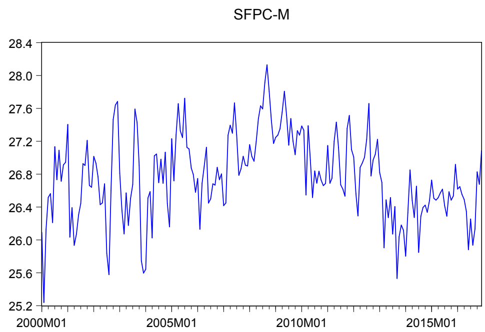
The four emotive word-pair difference indicators are then pooled with the five feature-based indicators, from which we extract a composite music-sentiment indicator as the



(a) Panel A: Time series of raw indicators



(b) Panel B: Time series of emotive word-pair difference indicators



(c) Panel C: Time series of composite music-sentiment indicators

Figure 1: Plots of music-sentiment indicators

Table 1: Correlation coefficients between indicators

Correlation t-Statistic Probability	DANCEABILITY	ENERGY	TEMPO	LOUDNESS	VALENCE	JOY	SADNESS	ANGER	FEAR	TRUST	DISGUST	ANTICIPATION	SURPRISE
DANCEABILITY	1.000000												
	—												
	—												
ENERGY	−0.055030	1.000000											
	−0.783315	—											
	0.4344	—											
TEMPO	−0.248655	0.194363	1.000000										
	−3.648640	2.816129	—										
	0.0003	0.0053	—										
LOUDNESS	−0.085524	0.534085	0.251599	1.000000									
	−1.219996	8.978589	3.694744	—									
	0.2239	0.0000	0.0003	—									
VALENCE	0.251454	0.699490	0.054886	0.193694	1.000000								
	3.692471	13.91131	0.781258	2.806050	—								
	0.0003	0.0000	0.4356	0.0055	—								
JOY	0.099312	0.052375	−0.039225	0.038148	0.056783	1.000000							
	1.418503	0.745405	−0.557926	0.542585	0.808336	—							
	0.1576	0.4569	0.5775	0.5880	0.4198	—							
SADNESS	−0.046018	0.012843	−0.037681	−0.054139	−0.008374	0.782291	1.000000						
	−0.654737	0.182554	−0.535931	−0.770584	−0.119019	17.84909	—						
	0.5134	0.8553	0.5926	0.4419	0.9054	0.0000	—						
ANGER	−0.001010	−0.056320	−0.089492	−0.005577	−0.062285	0.751211	0.880417	1.000000					
	−0.014348	−0.801737	−1.277047	−0.079260	−0.886959	16.17533	26.38771	—					
	0.9886	0.4236	0.2031	0.9369	0.3762	0.0000	0.0000	—					
FEAR	−0.008718	0.006250	−0.037860	0.035360	−0.017245	0.786334	0.925975	0.873835	1.000000				
	−0.123912	0.088826	−0.538479	0.502869	−0.245140	18.08979	34.85461	25.54284	—				
	0.9015	0.9293	0.5908	0.6156	0.8066	0.0000	0.0000	0.0000	—				
TRUST	0.038514	0.231980	−0.010897	0.093851	0.242923	0.871887	0.807958	0.772481	0.797802	1.000000			
	0.547790	3.389519	−0.154889	1.339782	3.559199	25.30459	19.48824	17.28877	18.80666	—			
	0.5844	0.0008	0.8771	0.1818	0.0005	0.0000	0.0000	0.0000	0.0000	—			
DISGUST	0.030088	0.097397	−0.115125	0.032174	0.090838	0.747424	0.877115	0.917235	0.878431	0.812638	1.000000		
	0.427821	1.390887	−1.647193	0.457522	1.296417	15.98998	25.95603	32.72616	26.12606	19.81877	—		
	0.6692	0.1658	0.1011	0.6478	0.1963	0.0000	0.0000	0.0000	0.0000	0.0000	—		
ANTICIPATION	−0.017683	0.100453	0.026551	0.076228	0.091770	0.903219	0.834173	0.812128	0.843481	0.916459	0.790806	1.000000	
	−0.251356	1.434964	0.377500	1.086571	1.309830	29.91080	21.49727	19.78223	22.31763	32.55286	18.36312	—	
	0.8018	0.1528	0.7062	0.2785	0.1917	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	—	
SURPRISE	−0.025755	0.088582	0.052054	0.101090	0.064536	0.856308	0.840155	0.830345	0.792937	0.862336	0.804429	0.920582	1.000000
	−0.366163	1.263957	0.740828	1.444151	0.919140	23.56486	22.01703	21.17800	18.49609	24.20543	19.24604	33.50124	—
	0.7146	0.2077	0.4597	0.1502	0.3591	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	—

First Principal Component, i.e. *SFPC-M*, according to the following equation:

$$\begin{aligned} SFPC\text{-}M =& 0.0437 danceability + 0.5223 energy + 0.2297 tempo + 0.3828 loudness \\ &+ 0.4578 valence + 0.2784 (joy\text{-}sadness) - 0.2489 (anger\text{-}fear) \\ &+ 0.1818 (anticipation\text{-}surprise) + 0.3793 (trust\text{-}disgust) \end{aligned} \tag{1}$$

Formulating the emotive word-pair indicators in terms of the ratio of basic-emotion scores instead of their differences has very little impact upon the *SFPC-M* composite indicator,[6] which suggests that our data-processing method is robust.

The time series of *SFPC-M* is plotted in Panel C of Figure 1.

The approach adopted in constructing *SFPC-M* follows the diffusion-index literature. This literature employs techniques to extract the common tendencies present in a collection of variables. These common tendencies are then recorded as diffusion indices, which can be used in subsequent empirical analysis to reduce dimentionality, overcome overfitting, and improve forecasting accuracy (see e.g. Stock and Watson 2002). Within the investor-sentiment literature, composite diffusion indices have been successfully utilized to predict stock-market returns. See e.g. Baker and Wurgler (2006, 2007), Huang et al. (2015), and Kaivanto and Zhang (2019).

We compare our composite music-sentiment indicator with the well-cited Baker and Wurgler sentiment index, which we denote as *SFPC-BW*. This is calculated as the first principal component of five standardized indirect investor-sentiment indicators — closed-end fund discount, number of IPOs, first day return of IPOs, equity issuance fraction in total financing, and difference between the market-to-book ratios of dividend payers and dividend non-payers — each orthogonalized with respect to a list of eight macroeconomic control variables.[7] Figure 2 plots the two time series, verifying a weak correlation ($\rho = -0.13$, p-value $= 0.06$). *SFPC-BW* has a higher sample variance,

[6] Using the ratio of emotive-word pairs results in a composite indicator that is highly correlated ($\rho = 0.99$) with the composite indicator based on using the arithmetic difference.

[7] Data obtained from Jeffrey Wurgler's online data base. As Wurgler argues, turnover is removed from Baker and Wurgler's (2006, 2007) original list of indicators, due to the large increase in trading volume that has resulted from the rapid growth of high-frequency trading.

however the variation is mostly due to large fluctuations during the internet-bubble crisis (2000–2002). Since 2002 the two composite indicators have demonstrated a similar time-series pattern — first an upward trend, then a downward trend triggered by the financial crisis, and finally stabilizing toward the end of our sample period. In transitioning from one regime to another, *SFPC-M* lags *SFPC-BW*.

We estimate VAR models for *SFPC-M* and *SFPC-BW*. Information criteria (AIC and BIC) recommend lag order 1 for both variables. No lead-lag predictability is found within the VAR system, indicating that our music-sentiment indicator contains information that is distinct from that already captured in the BW indicator.

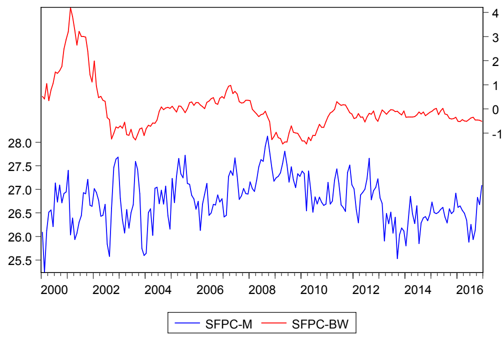


Figure 2: Plots of composite indicators

3 Music-based sentiment and market-return predictability

As one of the most fundamental and challenging topics in finance, market return predictability studies directly address the question of whether and how best to predict market returns, but also indirectly inform the related questions of (i) where market risk originates, and (ii) how market risk is priced. Answers to these questions in turn condition fundamental work on general equilibrium asset pricing models aiming to endogenize the market price of risk. To date, a variety of predictors have been studied in this literature, including fundamentals-based predictors such as the interest rate (Campbell 1987), past returns (Fama and French 1988), price-related ratios (Fama and French 1989;

Campbell and Shiller 1988), as well as predictors aiming to capture the behavioral, imperfectly rational effects of investor sentiment (Baker and Wurgler 2000, 2006; Tetlock 2007; Da, Engelberg and Gao 2015; Garcia 2013).[8]

In this section, we test whether our popular-music based sentiment indicator $SFPC$-M predicts aggregate stock-market returns. For benchmarking purposes, we also run the same analysis on two[9] further sentiment indicators — the Baker and Wurgler investor sentiment index ($SFPC$-BW), and the survey indicator $MICS$ from the University of Michigan Consumer Confidence Index.[10] Our choice of indicators contains a combination of direct survey indicator ($MICS$), indirect market indicators (from which $SFPC$-BW is extracted), and popular-music-borne emotional contagion indicators (from which $SFPC$-M is extracted).

3.1 Controlling for macroeconomic fundamentals

The music-sentiment indicator developed in Section 2.1 can be further refined through standardization and orthogonalization with respect to macroeconomic fundamentals. By doing so, we filter out potential confounding effects from macroeocnomic fundamentals through their correlation with both music sentiment and stock market returns. This also ensures that the emotion captured in the orthogonalized music-sentiment indicator constitutes *pure noise*, not *signal-plus-noise*.

We employ twelve fundamental variables: growth in industrial production; real growth in durable, non-durable, services and total consumption; growth rates in em-

[8]Delong et al (1990) show that as in the presence of noise traders and limits to arbitrage, investor sentiment may lead to market-wide mispricing.

[9]The Da, Engelberg and Gao (2015) FEARS index would ideally also be included. However given the manner in which FEARS is constructed, aggregating the daily index up to a monthly frequency is not straightforward. One method would be to compute the within-month-m average of the daily change in adjusted search volume recorded for each search term i, and then to compute the month m FEARS index as the sum of these averages across the $i \in \{1, 2, .., 30\}$ search terms: $FEARS_m = \Sigma_{i=1}^{30} R^i(\Delta ASVI_m)$. However, the authors make available only the daily index $FEARS_t$, not the underlying daily change in adjusted search volume for each search term i.

[10]University of Michigan Consumer Confidence Index is one of the most well-studied direct indicators of investor sentiment. $MICS$ is calculated as a linear transformation of five telephone survey questions. Lemmon and Portniaguina (2006) show the predictive power of $MICS$ in stock returns. Sabouni (2018) finds a long-run cointegration between $MICS$ and music-sentiment indicators.

ployment; CPI; NBER recession dummy variable; 1-month real US Treasury bill return; the difference between 3-month and 1-month real US treasury bill returns; the difference between 10-year and 3-month real US treasury bill returns; and the default spread between yields on Moody's Baa- and Aaa-rated corporate bonds. The first eight variables follow the consumption-based asset pricing literature (Baker and Wurgler 2006, 2007), and data are obtained from Jeffrey Wurgler's online database. The last four variables follow the conditional asset pricing literature (Brown and Cliff 2005), data for which are obtained from CRSP through Wharton Research Data Services.

We denote the orthogonalized music-sentiment indicator as $SFPC\text{-}M^{\perp}$. Similarly the orthogonalized survey indicator is denoted as $MICS^{\perp}$. Since in the construction of $SFPC\text{-}BW$ the first eight fundamental variables have already been orthogonalized out, in the present study we further orthogonalize $SFPC\text{-}BW$ with respect to the remaining four fundamental variables, to render it comparable with our music-sentiment indicator. We denote the fully orthogonalized Baker-Wurgler index as $SFPC\text{-}BW^{\perp}$.[11]

3.2 Model specification

We adopt two model specifications for our empirical investigation. In the first model, we run single-factor regressions as

$$\frac{1}{k}\sum_{i=1}^{k} r_{t+i} = c^{(k)} + \beta^{(k)} S_t + \epsilon_t^{(k)} \tag{2}$$

In the second model, we take into account the self-explanatory power of market returns and run double-factor regressions as

$$\frac{1}{k}\sum_{i=1}^{k} r_{t+i} = c^{(k)} + \alpha^{(k)}\left(\frac{1}{k}\sum_{i=1}^{k} r_{t-1+i}\right) + \beta^{(k)} S_t + \epsilon_t^{(k)} \tag{3}$$

In both model specifications:

[11] VAR regressions find no lead-lag relationship between $SFPC\text{-}M^{\perp}$ and $SFPC\text{-}BW^{\perp}$, again verifying that music-sentiment indicator contains information that is distinct from that already captured in the BW indicator. Moreover, VAR regression shows that $SFPC\text{-}M^{\perp}$ leads $MICS^{\perp}$ by two months.

(i) r refers to real return of value-weighted S&P 500 index;[12]

(ii) S represents a sentiment indicator and can refer to $MICS$, $MICS^{\perp}$, $SFPC\text{-}M$, $SFPC\text{-}M^{\perp}$, $SFPC\text{-}BW$ or $SFPC\text{-}BW^{\perp}$;

(iii) k represents the horizon length and can take the values of 1, 3, 12, 24, 36, or 48 as in Fama and French (1988).

(iv) the coefficient $\beta^{(k)}$ is the estimated sensitivity of the k-month-ahead return to the sentiment indicator. If $\beta^{(k)}$ is statistically significant then evidence of predictive power in the investor-sentiment indicator is present.

These long-horizon specifications have a number of advantages. First, as Summers (1986) argues, when market returns contain a persistent component, short-horizon tests will have very low power. Campbell (2011) shows that long-horizon regressions improve the power of hypothesis tests. Second, the multiple-horizon specification allows us to investigate the time-horizon over which investor sentiment becomes impounded into market prices. Third, the double-factor regressions in particular are capable of isolating the effect of investor sentiment on any k-month-ahead market return, independently of any effect that investor sentiment has had on preceding months' market returns. Combining results at multiple horizons together will provide a map of investor sentiment's effects on returns along the time line. This dimension has been under-studied in the literature to date.[13]

3.3 Results

Table 2 reports the results from estimating Equation (2) on horizons of 1, 3, 12, 24, 36, and 48 months. Table 3 reports the results from estimating Equation (3) on the same set of horizon lengths. For each regression, the coefficient estimate $\widehat{\beta^{(k)}}$ is reported, with

[12] Return data are obtained from CRSP through Wharton Research Data Services. Equal-weighted returns lead to no qualitative difference in results.

[13] Discussion of this aspect can be found in e.g. Baker and Wurgler (2006), however there are few formal tests in the literature.

the bootstrapped p-values in parentheses.[14]

Table 2: Coefficients and p-values in single-factor regressions

This table records the estimated coefficients $\hat{\beta}^{(k)}$ and p-values in the regression equation $\frac{1}{k}\sum_{i=1}^{k} r_{t+i} = c^{(k)} + \beta^{(k)} S_t + \epsilon_t^{(k)}$.

k	1 month	3 months	12 months	24 months	36 months	48 months
SFPC-M	-0.010656	-0.007980	-0.000905	0.001959	0.002313	0.002254
	(0.042*)	(0.072)	(0.421)	(0.259)	(0.141)	(0.103)
SFPC-M$^{\perp}$	-0.006418	-0.005469	-0.001616	0.00013	0.000422	-0.000226
	(0.038*)	(0.029*)	(0.198)	(0.443)	(0.327)	(0.407)
SFPC-BW	-0.009930	-0.009505	-0.011032	-0.008916	-0.005534	-0.004328
	(0.027*)	(0.027*)	(0.002**)	(0.000***)	(0.001**)	(0.001**)
SFPC-BW$^{\perp}$	-0.008646	-0.006583	-0.005170	-0.00179	0.000314	-0.000254
	(0.040*)	(0.065)	(0.075)	(0.236)	(0.462)	(0.432)
MICS	-0.000158	-0.000176	-0.000328	-0.000437	-0.000360	-0.000308
	(0.280)	(0.243)	(0.055)	(0.001**)	(0.000***)	(0.000***)
MICS$^{\perp}$	-0.000718	0.000505	0.000450	-0.001512	0.001207	-0.001266
	(0.455)	(0.447)	(0.454)	(0.302)	(0.293)	(0.239)

This table shows the coefficients of original sentiment indicators in regressions at six horizon lengths. Each indicator is used as the only regressor to explain real return of value-weighted S&P index at 1 month, 3 months, and 1, 2, 3, 4 years. The coefficients of sentiment indicators from the regressions are reported. The p-values in parentheses are obtained from the empirical distributions satisfying the null hypothesis in bootstrap simulations, using moving-block resampling of residuals. p-values below 5%, 1%, and 0.1% are denoted by one (*), two (**), and three (***) asterixes, respectively.

Several findings emerge from Tables 2 and 3.

First, our music-sentiment indicator predicts market returns, both before and after orthogonalization. *SFPC-M* and *SFPC-M*$^{\perp}$ have significant coefficients at 1-month and 3-months horizons in single-factor regressions. In double-factor regressions *SFPC-M* shows predictive power at 1-month and 1–4-year horizons, but after orthogonalization the long-horizon (1–4 year) predictability disappears, which suggests that the long-lasting effect mainly reflects beliefs about macroeconomic fundamentals.

Second, direct comparison of the music-sentiment and Baker-Wurgler indicators does not yield an unambiguous dominance relationship. *SFPC-BW* shows stronger perfor-

[14] We use a moving-block bootstrap to account for potential autocorrelation and heteroskedasticity in the residuals.

Table 3: Coefficients and p-values in double-factor regressions

This table records the estimated coefficients $\hat{\beta}^{(k)}$ and p-values in the regression equation $\frac{1}{k}\sum_{i=1}^{k} r_{t+i} = c^{(k)} + \alpha^{(k)}(\frac{1}{k}\sum_{i=1}^{k} r_{t-1+i}) + \beta^{(k)} S_t + \epsilon_t^{(k)}$.

k	1 month	3 months	12 months	24 months	36 months	48 months
$SFPC\text{-}M$	-0.010482	-0.001725	0.001067	0.000646	0.000165	0.000288
	(0.050*)	(0.347)	(0.000***)	(0.000***)	(0.265)	(0.000***)
$SFPC\text{-}M^{\perp}$	-0.006181	-0.001869	0.000506	0.000224	-0.000007	0.000033
	(0.042*)	(0.131)	(0.109)	(0.108)	(0.694)	(0.157)
$SFPC\text{-}BW$	-0.009181	-0.002866	-0.001177	0.000153	0.000032	0.000080
	(0.029*)	(0.041*)	(0.035*)	(0.329)	(0.417)	(0.234)
$SFPC\text{-}BW^{\perp}$	-0.008155	-0.001708	0.000133	0.000578	0.000198	0.000149
	(0.043*)	(0.237)	(0.429)	(0.031*)	(0.141)	(0.120)
$MICS$	-0.000146	-0.000110	-0.000071	-0.000050	-0.000022	-0.000027
	(0.297)	(0.173)	(0.052)	(0.003**)	(0.287)	(0.007**)
$MICS^{\perp}$	-0.001041	-0.000118	-0.000971	-0.000372	0.000070	-0.000175
	(0.445)	(0.487)	(0.109)	(0.198)	(0.436)	(0.210)

This table shows the coefficients of original sentiment indicators in regressions at six horizon lengths. Each indicator is used as a regressor along with lagged return to explain real return of value-weighted S&P index at 1 month, 3 months, and 1, 2, 3, 4 years. The coefficients of sentiment indicators from the regressions are reported. The p-values in parentheses are obtained from the empirical distributions satisfying the null hypothesis in bootstrap simulations, using moving-block resampling of residuals. p-values below 5%, 1%, and 0.1% are denoted by one (*), two (**), and three (***) asterixes, respectively.

mance than $SFPC\text{-}M$ in Table 2, but weaker performance across the full range of horizon lengths in Table 3. After orthogonalization, the predictive powers of the two indicators are indistinguishable at horizon lengths up to 12 months.

Third, coefficient signs for $SFPC\text{-}M$ show that in the short term (1- to 12-month horizons in Table 2 and 1-month to 3-month horizons in Table 3) sentiment predicts future market returns negatively. However in the long term there is a reverting effect, suggesting that S&P index drifts back to rationally priced levels in the long run. Yet none of these positive coefficients are statistically significant in single-factor regressions (Table 2), possibly as a result of diluted correlations due to moving-averaged returns. In double-factor regressions (Table 3) the long-term reversal becomes clear at horizons of 1 year and above.

Fourth, $MICS$ performs differently and less well than the $SFPC$ indicators. In the single-factor regressions (Table 2), the $MICS$ indicator's coefficients are significant over longer horizons rather than over shorter horizons. And these statistically significant coefficients are negative rather than positive. In double-factor regressions (Table 3), these characteristics are attenuated. Furthermore, the orthogonalized index $MICS^{\perp}$ does not achieve statistical significance at any horizon length. Overall, $SFPC\text{-}M^{\perp}$ out-performs $MICS^{\perp}$.

Finally, Table 3 shows that music sentiment predicts market returns in a manner consistent with noise trading acting on the emotional cues present in chart-topping popular music. The coefficient on $SFPC\text{-}M^{\perp}$ is negative and significant at the 1-month horizon and non-significant over longer horizons. The negative coefficient is consistent with a *noise-trading interpretation* (De Long et al. 1990). The component of music sentiment that is *pure noise* — in the sense of being orthogonal to fundamentals — is associated with an immediate market-price reaction, which subsequently dissipates, reversing over a 1-month period. Meanwhile, the coefficient on $SFPC\text{-}M$ is significant and negative at the 1-month horizon, but strongly significant and positive at the 12-, 24-, and 48-month horizons. In other words, the music-sentiment indicator $SFPC\text{-}M$ captures *signal-plus-noise* and is associated with a short-term noise-trading effect and a long-term signal-trading effect. To the extent that $SFPC$-M captures emotional contagion that is orthogonal to fundamentals, the associated aggregate trading activity — whether conducted by pop-music listeners or not — drives prices away from fundamentals temporarily. And to the extent that $SFPC$-M captures fundamentals, it is informative for trading horizons of 1, 2, and 4 years. But insofar as the coefficients at these longer horizons are positive and significant, traders are not fully exploiting the signal component within $SFPC$-M that reflects fundamentals. Either traders are not discerning the longer-horizon predictivity of music sentiment, or limits to arbitrage prevent this from being fully exploited.

Given the comparable performance of the music-sentiment and BW-sentiment indicators in Tables 2 and 3, we test whether the information contained in the music-sentiment indicator is redundant given the information already contained in the BW indicator. Since both orthogonalized indicators are statistically significant predictors of market returns at the 1-month horizon in Table 3, we test the redundancy hypothesis by regressing 1-month-ahead returns on current return, $SFPC$-$M^{\perp}$ and $SFPC$-$BW^{\perp}$. The following equation reports the results of this test. Both diffusion-index indicators are statistically significant at the 5% level, confirming their incremental, independent predictive power, and the associated F-test of overall significance rejects zero coefficients with $p = 0.021$.

$$\begin{array}{llllll} & r_{t+1} = 0.004761 & + \, 0.065246\, r_t & - \, 0.007249\, SFPC\text{-}M_t^{\perp} & - \, 0.012904\, SFPC\text{-}BW_t^{\perp} & + \, \epsilon_t \\ p\text{-value}: & [0.11] & [0.35] & [0.04] & [0.03] & \end{array}$$

In summary, results in this section validate our music-sentiment indicator as a predictor of market returns. Moreover, this predictive power persists after controlling for macroeconomic fundamentals and self-explanatory power, and is independent of the information contained in the widely cited Baker-Wurgler investor-sentiment indicator. The pattern of coefficient signs and their p-values across the range of horizon lengths is consistent with a short-term noise-trading interpretation of how emotional contagion present in popular music becomes impounded into market prices.

4 Time decomposition of market-return predictability

4.1 Time (in-)homogeneity

A legitimate concern is whether particular events within our sample period, such as the financial crisis, introduce discontinuities or regime changes in the underlying relationship between market return and music sentiment.[15] To test for this possibility, we implement the Bai-Perron (1998, 2003) multiple-breakpoint test on β in the regression equations

$$R_{t+1} = \alpha + \beta SFPC\text{-}M_t + \gamma ControlVariables_t + \epsilon_t \tag{4}$$

and

$$R_{t+1} = \alpha + \beta SFPC\text{-}M_t + \gamma ControlVariables_t + \theta R_t + \epsilon_t \tag{5}$$

where the control variables are the twelve macroeconomic fundamental variables discussed in Section 3. This test is capable of detecting multiple breaks at unknown dates. For this test, we retain the full 2000M1–2016M12 sample.

Results are summarized in Table 4. For both regressions, two breakpoints are indicated: 2002M9 and 2009M2 (starting months for the new regime). These dates coincide with the end of Internet Bubble Crisis and the recovery of confidence following the Financial Crisis.

To further investigate the effects of breakpoints, we report in Table 5 the coefficient estimates and associated p-values for β from Equations 4 and 5 across the full sample and each subsample as defined by the two breakpoints. Table 5 shows that after controlling for macroeconomic fundamentals, the effect of music sentiment on stock market returns is concentrated within the 2002M9–2009M1 period. For this subsample, the negative coefficient is statistically significant at the 5% level in Panel A, but non-significant (just)

[15] In the return-predictability literature, coefficient instability has been highlighted by e.g. Goyal and Welch (2003).

Table 4: Results of multiple breakpoint tests

Panel A: Regression equation $R_{t+1} = \alpha + \beta SFPC\text{-}M_t + \gamma Controls_t + \epsilon_t$.			
hypothesis test	F statistic	5% critical value	tested breakpoint
0 breakpoint vs 1 breakpoint	9.69	8.58	2002M9
1 breakpoint vs 2 breakpoints	32.21	10.13	2009M2
2 breakpoint vs 3 breakpoint	2.95	11.14	
Panel B: Regression equation $R_{t+1} = \alpha + \beta SFPC\text{-}M_t + \gamma Controls_t + \theta R_t + \epsilon_t$.			
hypothesis test	F statistic	5% critical value	tested breakpoint
0 breakpoint vs 1 breakpoint	9.13	8.58	2002M9
1 breakpoint vs 2 breakpoints	32.77	10.13	2009M2
2 breakpoint vs 3 breakpoint	3.10	11.14	

in Panel B. For the other two subsample periods, the linear relationship is not statistically significant.

4.2 Predictive power in expansions versus recessions

Note that the NBER recession dummy switches values near the breakpoint dates (2002M9 and 2009M2) from the Bai-Perron test,[16] suggesting that the predictive power of the music-sentiment indicator depends on the phase of the real-business cycle.[17] This is consistent with Garcia's (2015) finding that the effect of investor sentiment on stock-market prices is not symmetric across expansion and recession periods.

To test Garcia's hypothesis on our music-sentiment indicator, we run the following regressions and report the results in Table 6.

$$\begin{aligned} R_{t+1} =& \alpha + \beta_1[S_t(1 - RecessDummy_t)] + \beta_2[S_t RecessDummy_t] \\ &+ \gamma ControlVariables_t + \epsilon_t \end{aligned} \tag{6}$$

[16]The dummy variable changes from 1 to 0 in 2001M11, and from 1 to 0 in 2009M6.

[17]We verify that the results of multiple-breakpoint tests remain robust to exclusion of the recession dummy from the pool of control variables in Equations 4 and 5.

Table 5: Coefficient estimates and p-values for β across different sample periods

Panel A: Regression equation $R_{t+1} = \alpha + \beta SFPC\text{-}M_t + \gamma Controls_t + \epsilon_t$ across various sample periods.		
Sample period	$\widehat{\beta}$	p-value
2000M1–2016M12	-0.012526	0.070
2000M1–2002M8	-0.017597	0.557
2002M9–2009M1	-0.015980	0.049
2009M2–2016M12	-0.017450	0.165
Panel B: Regression equation $R_{t+1} = \alpha + \beta SFPC\text{-}M_t + \gamma Controls_t + \theta R_t + \epsilon_t$ across various sample periods.		
Sample period	$\widehat{\beta}$	p-value
2000M1–2016M12	-0.012225	0.078
2000M1–2002M8	-0.020155	0.496
2002M9–2009M1	-0.015674	0.055
2009M2–2016M12	-0.018458	0.142

and

$$
\begin{aligned}
R_{t+1} =& \alpha + \beta_1[S_t(1 - RecessDummy_t)] + \beta_2[S_t RecessDummy_t] \\
& + \gamma ControlVariables_t + \theta R_t + \epsilon_t
\end{aligned} \tag{7}
$$

where S refers to either $SFPC\text{-}M$ or $SFPC\text{-}M^{\perp}$. Control variables refer to the twelve macroeconomic fundamental variables as in Section 3.

Table 6 shows that 1-month-ahead market returns are more sensitive to music sentiment during recessions than during expansions. The $\hat{\beta}_2/\hat{\beta}_1$ ratio in Table 6 ranges from 3.39 to 6.00. Coefficients for $SFPC\text{-}M^{\perp}$ show that during recessions, a one-standard-deviation increase in the music-sentiment indicator will on average lead to a statistically significant 213–221-basis-point decrease in the 1-month-ahead S&P index return. In contrast, during expansions, a one-standard-deviation increase in the music-sentiment indicator will on average lead to a statistically non-significant 37-basis-point decrease in the S&P index return. Meanwhile, the same analysis run on $SFPC\text{-}BW$ and $SFPC\text{-}BW^{\perp}$ reveals no asymmetry between expansions and recessions.

Table 6: Coefficient estimates and p-values during expansions ($\hat{\beta}_1$) and recessions ($\hat{\beta}_2$) 2000M1–2016M12.

Panel A: Regression equation $R_{t+1} = \alpha + \beta_1[S_t(1 - RecessDummy_t)] + \beta_2[S_t RecessDummy_t] + \gamma ControlVariables_t + \epsilon_t$.

	$\widehat{\beta_1}$	p-value$_1$	$\widehat{\beta_2}$	p-value$_2$
$S = SFPC\text{-}M_t$	-0.009361	0.201	-0.033602	0.060
$S = SFPC\text{-}M_t^{\perp}$	-0.003685	0.334	-0.022097	0.021

Panel B: Regression equation $R_{t+1} = R_{t+1} = \alpha + \beta_1[S_t(1 - RecessDummy_t)] + \beta_2[S_t RecessDummy_t] + \gamma ControlVariables_t + \theta R_t + \epsilon_t$.

	$\widehat{\beta_1}$	p-value$_1$	$\widehat{\beta_2}$	p-value$_2$
$S = SFPC\text{-}M_t$	-0.009367	0.201	-0.031796	0.079
$S = SFPC\text{-}M_t^{\perp}$	-0.003688	0.334	-0.021324	0.027

5 Out-of-sample forecasting performance

In this section we evaluate the out-of-sample (OOS) predictive power of our orthogonalized music-sentiment indicator ($SFPC\text{-}M^{\perp}$), as benchmarked to that of a passive sample-mean forecasting model.[18] We repeat the analysis for the same two competing sentiment indicators employed in Section 3, i.e. the Baker and Wurgler sentiment index ($SFPC\text{-}BW^{\perp}$) and the University of Michigan Consumer Confidence Index ($MICS^{\perp}$). The horse race among these three competing investor sentiment indicators sheds light on their relative OOS predictive strength.

We employ two operationalizations of a linear forecasting model. In the first approach, the starting point of the estimation sample is fixed at the sample starting date, i.e. 2000M1. For each month-T forecast, OLS is estimated with all available information (from 2000M1 to month $T-1$). We reserve 60 months from the beginning of the full data sample as the initial estimation sample.[19] We call this approach the rolling-and-recalibrating model.

In the second approach, the window length of the estimation sample is fixed (at 60 months), and for each month-T forecast, OLS is estimated with available information in

[18] We subtract OOS cumulative squared errors of the passive sample-mean forecasting model from the OOS cumulative squared errors of our linear forecasting model. The difference is denoted as 'Benchmarked CumSE'.

[19] Our results are robust to the length of the reserved initial estimation sample, e.g. 60 months.

the past 60 months (from month $T-60$ to month $T-1$).[20] We call this approach the rolling-window model.

The main results are summarized in Figure 3. Panel A and Panel B represent the rolling-and-recalibrating model and the rolling-window model, respectively. Benchmarked CumSE values are plotted. For a given investor-sentiment indicator, positive (benchmarked) CumSE indicates that the linear forecasting model under-performs the sample-mean forecasting model, while negative (benchmarked) CumSE indicates that the linear forecasting model out-performs the sample-mean forecasting model.

Several findings emerge.

First, the three investor-sentiment indicators initially perform comparably well, but from 2008 onwards their prediction errors diverge.

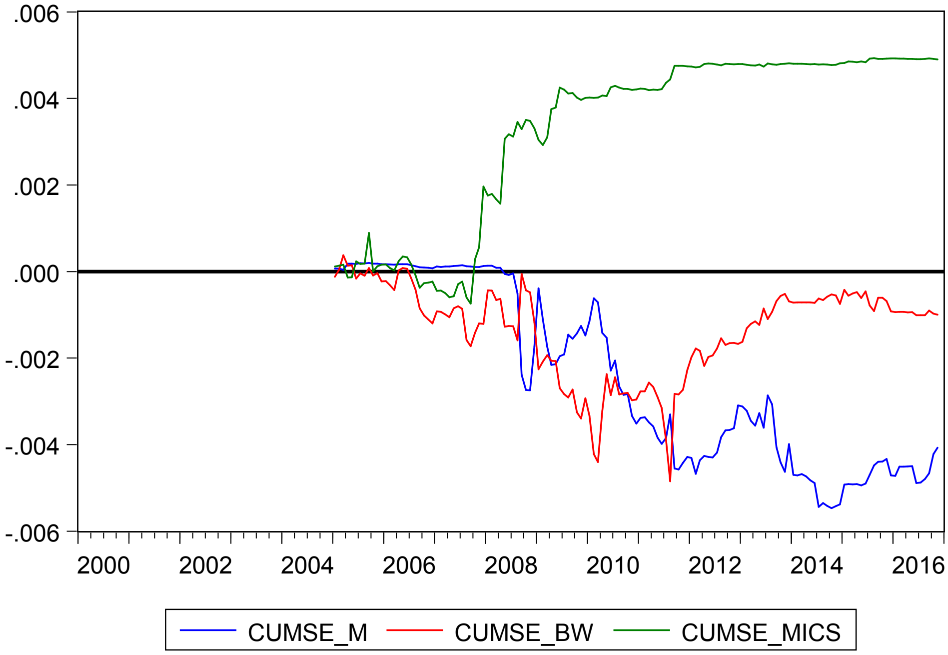
Second, overall $SFPC\text{-}M^{\perp}$ outperforms sample-mean forecasting in both forecasting operationalizations, $MICS^{\perp}$ under-performs sample-mean forecasting in both operationalizations, in line with its weak in-sample (IS) predictive power in Section 3, and $SFPC\text{-}BW^{\perp}$ out-performs sample-mean forecasting in the rolling-and-recalibrating model, but fails to do so in the rolling-window model.

Third, overall $SFPC\text{-}M^{\perp}$ displays forecasting power that is at least equal to that of $SFPC\text{-}BW^{\perp}$. From 2010 $SFPC\text{-}M^{\perp}$ largely outperforms $SFPC\text{-}BW^{\perp}$: in rolling-window forecasting $SFPC\text{-}M^{\perp}$ consistently outperforms $SFPC\text{-}BW^{\perp}$; in rolling-and-recalibrating forecasting $SFPC\text{-}M^{\perp}$ consistently outperforms $SFPC\text{-}BW^{\perp}$ with the exception of one month (2011M8).

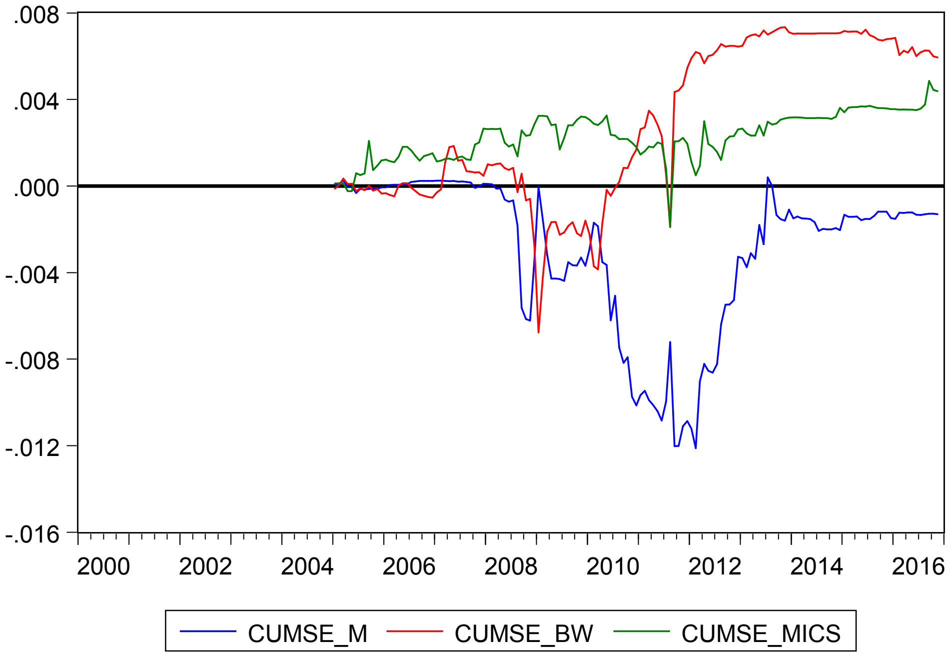
Fourth, for rolling-window forecasting, prediction errors rise rapidly for all indicators between late-2011 and late-2013. This implies that sentiment-indicator data that became available 60 months earlier — i.e. data from 2005 to 2008 — particularly fail to predict market returns. For rolling-and-recalibrating forecasting, the same phenomenon shows up for the period, but to a lesser degree. The latter model retains all earlier data, and thus leads to more gradual changes in estimated coefficients and prediction errors.

Finally, it is noteworthy that from mid-2008 onward our music-sentiment indicator

[20]Our results are robust to the length of rolling window, e.g. 60 months.



(a) Panel A: Benchmarked Cumulative Squared Errors from a rolling-and-recalibrating model



(b) Panel B: Benchmarked Cumulative Squared Errors from a rolling-window model

Figure 3: Cumulative out-of-sample prediction errors

$SFPC\text{-}M^{\perp}$ consistently out-performs sample-mean forecasting. This finding stands in contrast to the results of Welch and Goyal (2008), who utilize annual data from 1871 to 2005 to find that multiple equity-premium predictors universally fail to beat sample-mean forecasting. The strong OOS predictive power of $SFPC\text{-}M^{\perp}$ further validates our conjecture that the emotional content of popular music becomes impounded into market prices.

In Section 3 we report that the IS predictive power of $SFPC\text{-}M^{\perp}$ is non-redundant with respect to $SFPC\text{-}BW^{\perp}$. In the present section, we also investigate whether such predictive power remains non-redundant in OOS forecasting. Since $SFPC\text{-}BW^{\perp}$ successfully outperforms the benchmark sample-mean model in rolling-and-recalibrating forecasting, we add $SFPC\text{-}M^{\perp}$ into this model and examine whether inclusion of this additional predictor will further improve forecasting performance. The CumSE of this double-factor forecasting model is plotted in Figure 4 (as $CumSE\_M\_BW$), against the three CumSE curves from single-factor forecasting as in Figure 3 ($CumSE\_M$, $CumSE\_BW$ and $CumSE\_MICS$).[21]

Figure 4 shows that $CumSE\_M\_BW$ remains comparable to $CumSE\_BW$ until late-2008. From then onward the double-factor model consistently outperforms the single-factor model. Furthermore, $CumSE\_M\_BW$ also remains lower than $CumSE\_M$ throughout most of the sample period. In summary, pooling the music-sentiment indicator with the Baker-Wurgler sentiment indicator further mitigates forecasting errors, once again validating our previous finding that the music-sentiment indicator is not statistically redundant, and retains independent predictive power even after controlling for $SFPC\text{-}BW^{\perp}$.

[21] As $SFPC\text{-}BW^{\perp}$ fails to forecast market return in rolling-window model as benchmarked to sample-mean, it is less interesting to further add $SFPC\text{-}M^{\perp}$ into the model, which will likely suffer from not only estimation error but also decrease of forecasting power due to overfitting.

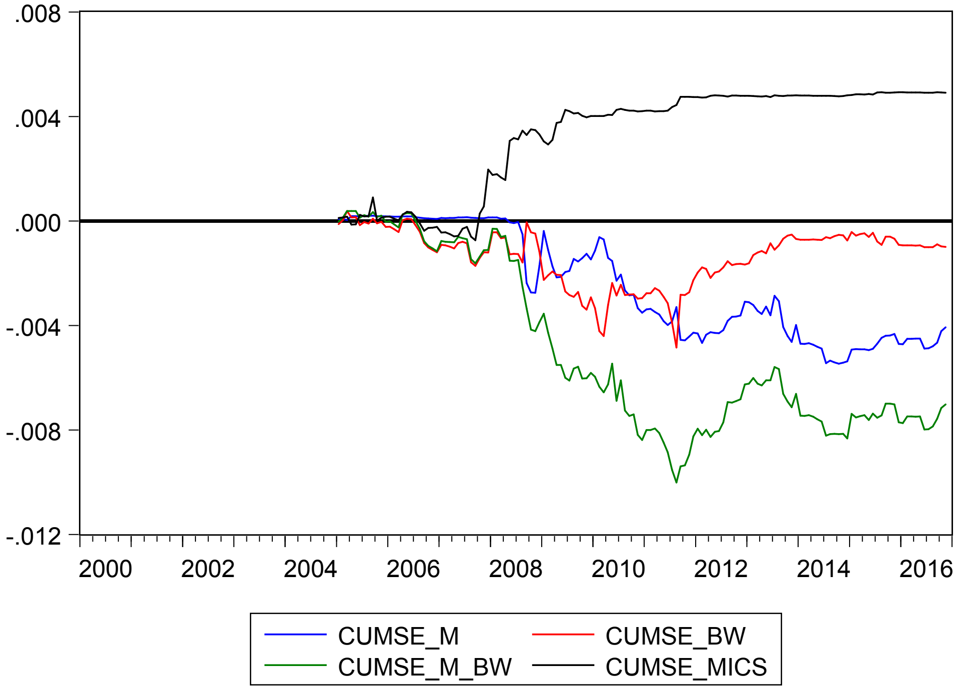


Figure 4: Benchmarked Cumulative Squared Errors from a rolling-and-recalibrating model

6 Cross-sectional analysis

We extend the analysis by investigating the effect of music sentiment on cross-sectional stock returns in the spirit of Fama and French (1993, 2015).

Specifically, we study the value-weighted returns for quintile portfolios consisting all available NYSE, AMEX and NASDAQ stocks, sorted by risk proxies, price-related ratios and operating indicators. The list of sort variables is presented in Table 7. NYSE breakpoints at the end of each June are used to segment the quintiles. More details on the data are available from Kenneth French's online data library.

Table 7: List of sort variables

SORT VARIABLE	DEFINITION
Beta	market beta
ME	market equity
B/M	BookEquity/MarketEquity ratio
Inv	annual growth rate in total assets
OP	annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses divided by book equity
Volatility	variance of daily returns
D/P	Dividend/Price ratio
E/P	Earnings/Price ratio
CF/P	CashFlow/Price ratio
Accruals	annual change in operating working capital per split-adjusted share divided by book equity per share

As Baker and Wurgler (2006, 2007) argue, investor sentiment might affect cross-sectional stock returns through two overlapping channels: (i) some stocks are more difficult to value; and (ii) some stocks are more difficult to arbitrage. Utilizing U.S. stock price data from 1963 to 2001, they show that small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks and distressed stocks have subsequent returns that are negatively correlated with the diffusion index of six indirect investor-sentiment indicators ($SFPC$-BW). Using more recent data, we test whether these effects generalize to the new diffusion index of music-sentiment indicators.

6.1 Cross-sectional returns conditional on music sentiment

We report in Table 8 the average returns of quintile portfolios, arranged by sort variables and the music-sentiment indicator ($SFPC\text{-}M^{\perp}$) in the previous month. We operationalize comparisons between periods of 'high sentiment' and 'low sentiment' in two different ways: top half vs. bottom half, and top quintile vs. bottom quintile. The former makes use of all data contained in the sample, while the latter emphasizes the effects of extreme sentiment levels.

Multiple general conclusions can be drawn.

First, unconditional average returns (reported as full-sample average returns) confirm a wide range of established patterns in the literature on cross-sectional stock returns, including: size effect, value premium, profitability premium, investment discount, dividend premium, and excess volatility puzzle.

Second, during periods of low music sentiment, subsequent monthly returns are generally expected to be higher than unconditional means; during periods of high music-sentiment the reverse is true. Such conditional divergence is consistent with the finding in Section 3 that music-sentiment indicators predict negative 1-month-ahead aggregate returns. This is consistent with sentiment-driven trading being either a pure noise-trading phenomenon or an overshooting phenomenon.

Third, by calculating the differences between average returns during low-sentiment periods and high-sentiment periods, we draw conclusions on how the effect of sentiment varies. A large difference verifies high sensitivity to music sentiment. Our estimates confirm Baker and Wurgler's (2006) findings that small stocks (Q1-ME), high-volatility stocks (Q5-Volatility), unprofitable stocks (Q1-OP, Q1-E/P, and Q1-CF/P), non-dividend-paying stocks (Q1-D/P), and extreme growth stocks (Q1-B/M) are more responsive to (music) sentiment. However our results do not show that distressed firms (Q5-B/M) are particularly affected by music sentiment. Yet we do find that stocks with high market beta values (Q1-Beta) tend to be heavily affected by music sentiment.

Fourth, portfolio returns computed across different sort variables suggest that the effects of music-sentiment are not homogeneous across periods of low and high sentiment.

Table 8: Average subsequent monthly returns (%) by music-sentiment and sort variables

Sort Variable	Quintile	Full sample	$SFPC\text{-}M^{\perp}$ (0%, 50%]	$SFPC\text{-}M^{\perp}$ (50%, 100%]	Δ	$SFPC\text{-}M^{\perp}$ (0%, 20%]	$SFPC\text{-}M^{\perp}$ (80%, 100%]	Δ
Beta	Q1	0.68	0.87	0.48	0.39	0.79	0.17	0.62
	Q2	0.79	1.00	0.57	0.43	1.10	0.37	0.73
	Q3	0.67	0.87	0.45	0.42	1.49	0.02	1.47
	Q4	0.63	0.86	0.39	0.46	1.27	0.12	1.15
	Q5	0.38	0.66	0.09	0.56	1.27	-0.16	1.43
ME	Q1	0.78	1.14	0.42	0.71	1.30	1.14	0.16
	Q2	0.82	0.96	0.69	0.28	1.09	1.12	-0.02
	Q3	0.83	1.01	0.65	0.36	1.11	0.74	0.37
	Q4	0.79	0.97	0.61	0.36	1.15	0.55	0.60
	Q5	0.46	0.65	0.28	0.37	0.90	-0.12	1.02
B/M	Q1	0.42	0.60	0.23	0.37	0.93	-0.34	1.28
	Q2	0.76	0.89	0.64	0.25	1.09	0.38	0.71
	Q3	0.88	1.11	0.65	0.46	1.28	0.61	0.66
	Q4	0.72	1.00	0.43	0.58	0.79	0.51	0.28
	Q5	0.92	1.11	0.73	0.38	1.73	1.26	0.47
Inv	Q1	0.85	1.10	0.61	0.49	1.10	0.30	0.80
	Q2	0.69	0.80	0.57	0.22	0.89	0.31	0.58
	Q3	0.71	0.89	0.52	0.37	0.98	0.33	0.64
	Q4	0.57	0.79	0.34	0.45	1.14	0.07	1.07
	Q5	0.31	0.56	0.05	0.50	0.96	-0.35	1.32
OP	Q1	0.09	0.45	-0.28	0.73	0.76	-0.40	1.16
	Q2	0.54	0.78	0.29	0.49	0.91	0.03	0.88
	Q3	0.60	0.71	0.49	0.23	0.79	0.34	0.45
	Q4	0.62	0.80	0.44	0.36	1.20	0.04	1.15
	Q5	0.64	0.78	0.49	0.29	1.02	0.11	0.92
Volatility	Q1	0.68	0.91	0.45	0.46	1.02	0.15	0.88
	Q2	0.74	1.05	0.43	0.61	1.30	0.09	1.21
	Q3	0.65	0.91	0.38	0.52	1.14	0.15	0.98
	Q4	0.73	1.11	0.34	0.77	1.48	0.17	1.31
	Q5	0.09	0.58	-0.40	0.98	0.65	0.11	0.54
D/P	Q1	0.35	0.60	0.09	0.52	1.07	-0.48	1.55
	Q2	0.67	0.93	0.40	0.53	1.09	0.09	1.01
	Q3	0.77	0.95	0.58	0.38	1.07	0.12	0.94
	Q4	0.85	0.97	0.73	0.24	1.08	0.43	0.65
	Q5	0.89	1.08	0.68	0.40	1.13	0.76	0.37
E/P	Q1	0.43	0.77	0.09	0.69	1.18	-0.28	1.46
	Q2	0.68	0.83	0.52	0.31	1.01	-0.09	1.10
	Q3	0.71	0.82	0.60	0.22	1.07	0.32	0.75
	Q4	0.82	1.09	0.55	0.54	1.26	0.25	1.00
	Q5	1.05	1.14	0.95	0.19	1.28	1.28	0.00
CF/P	Q1	0.45	0.76	0.14	0.62	1.19	-0.44	1.63
	Q2	0.70	0.84	0.55	0.29	0.95	0.14	0.81
	Q3	0.69	0.84	0.53	0.31	1.05	0.29	0.75
	Q4	0.96	1.25	0.66	0.59	1.34	0.53	0.80
	Q5	0.85	0.86	0.84	0.02	1.04	1.15	-0.10
Accruals	Q1	0.58	0.79	0.36	0.42	1.19	-0.05	1.24
	Q2	0.53	0.70	0.36	0.33	1.11	-0.02	1.13
	Q3	0.53	0.68	0.38	0.30	0.84	0.07	0.78
	Q4	0.64	0.77	0.51	0.26	0.66	0.12	0.55
	Q5	0.52	0.58	0.47	0.11	0.77	0.38	0.39

Baker and Wurgler (2006) report that during 1963–2001, the cross sectional effects of investor sentiment tend to flip signs between the periods of low and high sentiment, for almost all sort variables. For example, they report that first-decile ME earns higher returns than tenth-decile ME during the period of low sentiment, but lower returns during the period of high sentiment. We observe the same sign-flipping effect only with portfolios sorted by CF/P, Accruals, and Market Beta. Portfolios sorted by D/P and E/P show more diverse sensitivities to music-sentiment during periods of high sentiment than during periods of low sentiment. For the remaining sort variables, time inhomogeneity is not present in the 2000–2016 sample.

Fifth, we observe a U-shaped effect in portfolios sorted by the two additional 2015 Fama-French risk factors, i.e. Inv and OP. Both Q1 and Q5 stocks are more affected by music-sentiment, while the middle Q2–Q4 stocks remain less affected.

We now discuss in detail the portfolio returns associated with each sort variable in turn.

(i) Beta — Unconditional average returns are of comparable magnitude across Q1–Q4. The exception is Q5, which reflects high demand from investor and thus lower subsequent returns (0.38%).

    Such a sudden drop in the highest quintile persists when we divide the full sample into bottom-50%-sentiment periods and top-50%-sentiment periods. Q5 seems to be slightly more affected by music-sentiment (difference between two sub-samples valued 0.56% for Q5-Beta, higher than 0.39-0.46% from Q1-beta to Q4-beta stocks).

    Starker contrasts emerge when focusing on the extremes of sentiment. During periods of bottom-20% sentiment, average returns are 0.79% for Q1-beta stocks, and 1.27% for Q5-beta stocks. During periods of top-20% sentiment, average returns are 0.17% for Q1-beta stocks, and -0.16% for Q5-beta stocks. The cross-sectional effect of music-sentiment flips signs across the two extreme periods.

(ii) ME — Unconditional average returns confirm the size effect as in Fama and French (1993).

Dividing the full sample into bottom- and top-50%-sentiment periods, we find that small firms are more responsive to the effect of music-sentiment. Q1-ME earns an average subsequent monthly return of 1.14% when sentiment is low, and 0.42% when sentiment is high, leading to a difference of 0.71%. Q5-ME has a much lower difference of 0.37%. This finding suggests that compared to Q5-ME, demand for Q1-ME stocks falls more drastically during low-sentiment periods. When sentiment is high, demand rises again for small firms.

Focusing on the extremes yields further insight. When sentiment rises into the top-20% range, market demand for bottom-size-quintile (Q1-ME) firms falls, leading to higher expected subsequent returns (1.14%). Returns are lower in each successive size quintile, eventually falling to -0.12% in Q5-ME. Thus, when sentiment is in the top-20% range, demand is strongly skewed toward mid- and large-size firms (Q3-ME, Q4-ME, Q5-ME).

(iii) B/M — Unconditional average returns confirm the value premium as in Fama and French (1993).

Dividing the full sample into bottom- and top-50%-sentiment periods does not yield a clear conclusion on how sentiment affects growth stocks, value stocks and middle stocks. The value premium persists for both halves of our full sample.

It is only during sentiment extremes that growth stocks rise into or fall out-of favor. For Q1-B/M stocks, returns are 1.28% higher when sentiment is in the bottom-20% range than when sentiment is in the top-20% range.

Return sensitivity to music-sentiment — as gauged by the difference in portfolio returns between bottom- and top-20% sentiment periods — increases from Q5-B/M to Q1-B/M. This finding is different from that in Baker and Wurgler (2006), who consider value stocks as stocks in distress and find that both growth stocks and value stocks are sensitive to investor sentiment for the period of 1963-2001.

(iv) Inv — Unconditional average returns confirm the investment discount as in Fama and French (2015). Conservative firms (Q1-Inv) yield a 0.85% monthly unconditional return, while aggressive firms (Q5-Inv) yield a 0.31% monthly unconditional return.

We find a U-shape for the sensitivity of quintile returns to music-sentiment. Returns of conservative firms and aggressive firms are both more responsive to music-sentiment than intermediate-range firms. This U-shape is manifest in both the bottom- and top-50% data as well as the bottom- and top-20% data.

(v) OP — Unconditional average returns confirm the profitability premium as in Fama and French (2015).

Less profitable firms demonstrate higher sensitivity to the effect of music-sentiment when gauged by the contrast between low- and high-sentiment halves of the sample. However when sentiment extremes are the focus, we find a U-shape similar to portfolios sorted by investment.

(vi) Volatility — Unconditionally, the combination of low average return and high Q5-volatility is in line with the excess volatility puzzle.

With sentiment partitioned into below- and above-median categories, sensitivity to sentiment increases from Q1- to Q5-Volatility. Although the difference in expected returns for Q5-volatility between bottom- and top-50% sentiment is larger than for Q1–Q4, this occurs at a much lower level, i.e. 0.58% for bottom-50% sentiment and -0.4% for top-50% sentiment. The latter negative return suggests strong over-purchasing of Q5-Volatility stocks.

When sentiment rises into the top-20% range, demand recedes and prices fall, whereby the expected return increases to 0.11%.

(vii) D/P — It has been long found that dividend-payers (low price-dividend-multiple firms) enjoy a premium in expected returns. Our unconditional averages confirm this effect.

Conditional on high music-sentiment — either above-median or top-20% sentiment — expected returns are lowest for Q1-D/P (high price-dividend-multiple firms) and highest for Q5-D/P (low price-dividend-multiple firms). There is less variation in expected return within the low-sentiment categories. Average monthly returns stay within the stable range of 1.07-1.13% across D/P quantiles when sentiment is very low, but vary between -0.48% for dividend non-payers and 0.76% for dividend payers when sentiment is very high, i.e. a total range of 1.24%.

Additionally, there is strong evidence that high price-dividend-multiple firms (Q1-D/P) have expected returns that are more responsive to music-sentiment.

(viii) E/P — The behaviour of portfolios sorted by E/P is analogous to those sorted by D/P. Conditional on high music-sentiment, the earnings premium increases between Q1-E/P and Q5-E/P. For top-20% sentiment, this increase runs from -0.28% to 1.28%, i.e. a total range of 1.56%. Low price-earnings-multiple firms (Q5-E/P) have precisely zero sensitivity to music-sentiment extremes, while high price-earnings-multipe firms (Q1-E/P) have strong (1.46%) sensitivity to music-sentiment extremes.

(ix) CF/P — Unconditional averages suggest that firms with low relative cash flow (high price-cash-flow multiples) tend to have lower monthly returns.

There is also evidence that the cross-sectional effect of music-sentiment is not homogeneous during low- and high-sentiment periods. For bottom-50%-sentiment periods, average returns stay relatively stable, while for top-50%-sentiment periods average returns increase from 0.14% for firms with low relative cash flow to 0.84% for firms with high relative cash flow.

Focusing on extreme-sentiment periods, we find even stronger evidence of conditional non-homogeneous effects. For bottom-20% sentiment periods, Q1-CF/P firms earn higher average returns (1.19%) than Q5-CF/P (1.04%); for top-20%-sentiment periods, the relationship is consistent with that found for D/P and E/P, running from -0.44% for Q1-CF/P to 1.15% for Q5-CF/P, i.e. a total range of 1.59%.

Additionaly, we find strong evidence that firms with low relative cash flow (high price-cash-flow multiples) have expected returns that are more responsive to music-sentiment.

(x) Accruals — There is no apparent pattern in unconditional average returns of portfolios sorted by Accruals.

However, conditional on music-sentiment, we find sign-flipping cross-sectional patterns. When sentiment is low, Q1-Accruals firms earn higher returns (0.79% for bottom-50% and 1.19% for bottom-20%) than Q5-Accruals (0.58% for bottom-50% and 0.77% for bottom-20%). When sentiment is high, Q1-Accruals firms earn lower returns (0.36% for top-50% and -0.05% for top-20%) than Q5-Accruals (0.47% for top-50% and 0.38% for top-20%).

It is also clear that firms with low Accruals are more sensitive to music-sentiment.

6.2 Explaining long-short strategy returns with music-sentiment indicators

In this section, we implement a further test of the explanatory power of music-sentiment indicators in the cross-section of stock returns. Specifically, we construct a hypothetical trading strategy that buys one unit of the Q1 portfolio ('long') while selling one unit of the Q5 portfolio ('short') as sorted by one of the aforementioned variables.[22] We first regress the monthly returns of this trading strategy on Fama and French's (2015) five factors — excess market return, small-minus-big, value-minus-growth, investment, and profitability — and we record the associated regression residuals as our target variables. Then we investigate whether our music-sentiment indicators have explanatory power in the cross-section of stock returns that is incremental to the Fama-French factors, by estimating the following equation:

$$Residual_t = \alpha + \beta_0 S_t + \sum_{i=1}^{k} \beta_i S_{t-i} + \epsilon_t \tag{8}$$

[22] Such a long-short strategy based on a specific firm characteristic is in keeping with the notion that consumers view goods as a combination of salient characteristics, dating back to Lancaster (1966). Similar hypothetical trading can be found in e.g. Baker and Wurgler (2006).

where:

(i) $Residual_t$ refers to the residuals from regressing (a) the monthly return of the long-short strategy based on one of the ten sort variables in Table 7, on (b) the five Fama-French factors;

(ii) S_t represents the music-sentiment indicator, either $SFPC\text{-}M_t$ or $SFPC\text{-}M_t^{\perp}$;

(iii) k captures the lasting effect of past sentiment on the cross-section of stock returns, of which we consider values up to 6;

(iv) the coefficient β_0 captures the sensitivity of the target variable to the contemporaneous music-sentiment indicator.

(v) the coefficient β_i captures the sensitivity of the target variable to the i-months-lagged music-sentiment indicator.

This model simultaneously tests for the effect of both contemporaneous music-sentiment and past music-sentiment. It also enables us to examine the time lag with which past sentiment becomes impounded into the cross-section of stock returns, which is relatively under-studied in the literature.

Based on theoretical predictions (e.g. DeLong et al. 1990), and incorporating the empirical findings from Section 5.1, we specify the following null hypotheses:

(i) The targeted residuals of the long-short trading strategy, after orthogonalization with respect to the five Fama-French factors, are uncorrelated with contemporaneous music sentiment, i.e. $H_0 : \beta_0 = 0$.

(ii) The targeted residuals of the long-short trading strategy, after orthogonalization with respect to the five Fama-French factors, are uncorrelated with all past music sentiment, i.e. $H_0 : \beta_i = 0$ for $i = 1...k$.

The associated alternative hypotheses are as follows:

(a.i) The trading strategy that is long in portfolios that are more (less) sensitive to music-sentiment and short in portfolios that are less (more) sensitive to music-sentiment is expected to have returns positively (negatively) associated with contemporaneous music-sentiment, i.e. $\beta_0 > 0$ ($\beta_0 < 0$).

(a.ii) The trading strategy that is long in portfolios that are more (less) sensitive to music-sentiment and short in portfolios that are less (more) sensitive to music-sentiment is expected to have returns negatively (positively) associated with past music-sentiment, i.e. $\beta_i < 0$ ($\beta_i > 0$) for $i = 1...k$.

We report the regression results in Table 9. For each sort variable, we first select the optimal value for k based on information criteria including AIC, BIC and H-Q values. Then we estimate the corresponding equation using the optimal k, and report the estimated coefficients and associated p-values.

In summary, the results support a statistically significant linear relationship between the trading-strategy returns and music-sentiment indicators. Returns to long-short trading strategies based on firm characteristics are explainable by music sentiment for eight out of ten sort variables. Five sort variables provide long-short strategy returns that are explained by music-sentiment indicators both before and after orthogonalization, including market beta (Beta), size (ME), investment (Inv), volatility (Volatility), and earnings/price ratio (E/P). The Accruals-shorting strategy earns returns which are explained by $SFPC\text{-}M$, but the significant linear relationship disappears once macroeconomic fundamentals are controlled for. Strategies that short profitability (OP) and cash flow (CF/P) have expected returns significantly predicted only by $SFPC\text{-}M^{\perp}$.

Our estimates reject null-hypothesis (i) and find explanatory power in contemporary music-sentiment for strategies that trade on Beta, Volatility and Accruals. Results from Section 5.1 show that firms with high market Beta, high Volatility and low Accruals tend to be more affected by music-sentiment, consistent with significant negative $\hat{\beta}_0$ for Beta and Volatility, and significant positive $\hat{\beta}_0$ for Accruals in Table 9.

Suppose that an increase in investor sentiment, coinciding with a shift in the emo-

Table 9: Predicting long-short strategy returns with music-sentiment indicators

We report coefficient estimates and p-values in regressing equation $Residual_t = \alpha + \beta_0 S_t + \sum_{i=1}^{k} \beta_i S_{t-i} + \epsilon_t$. Optimal value for k is based on information criteria including AIC, BIC and H-Q values.

	$S = SFPC\text{-}M$								$S = SFPC\text{-}M^{\perp}$							
Sort Variable	Optimal k	$\hat{\beta}_0$ (p-value)	$\hat{\beta}_1$ (p-value)	$\hat{\beta}_2$ (p-value)	$\hat{\beta}_3$ (p-value)	$\hat{\beta}_4$ (p-value)	$\hat{\beta}_5$ (p-value)	$\hat{\beta}_6$ (p-value)	Optimal k	$\hat{\beta}_0$ (p-value)	$\hat{\beta}_1$ (p-value)	$\hat{\beta}_2$ (p-value)	$\hat{\beta}_3$ (p-value)	$\hat{\beta}_4$ (p-value)	$\hat{\beta}_5$ (p-value)	$\hat{\beta}_6$ (p-value)
Beta	0	-1.5719							1	-0.8211	0.4834					
		(0.001*)								(0.019*)	(0.156)					
ME	6	-0.2539	-0.1840	0.3739	-0.2981	0.2556	-0.6039	0.4788	6	-0.1245	-0.1381	0.2538	-0.1976	0.0524	-0.2673	0.2162
		(0.261)	(0.484)	(0.156)	(0.259)	(0.334)	(0.021*)	(0.032*)		(0.294)	(0.305)	(0.058)	(0.141)	(0.696)	(0.048*)	(0.063)
B/M	0	-0.2555							0	0.0404						
		(0.171)								(0.718)						
Inv	5	0.0693	0.0690	0.0104	-0.6474	0.4010	0.1865		4	0.0608	0.0273	-0.0374	-0.3118	0.2756		
		(0.764)	(0.800)	(0.970)	(0.019*)	(0.136)	(0.412)			(0.618)	(0.844)	(0.787)	(0.026*)	(0.022*)		
OP	4	0.0009	0.2146	-0.5749	0.0871	0.4203			3	-0.1615	0.1209	-0.3263	0.0715			
		(0.997)	(0.486)	(0.064)	(0.773)	(0.102)				(0.239)	(0.439)	(0.038*)	(0.595)			
Volatility	0	-1.4565							0	-0.6823						
		(0.003*)								(0.020*)						
D/P	0	0.1768							0	-0.0397						
		(0.704)								(0.887)						
E/P	1	0.6339	-0.9860						1	0.2046	-0.5709					
		(0.107)	(0.013*)							(0.337)	(0.007*)					
CF/P	1	0.2424	-0.8228						1	-0.0121	-0.5234					
		(0.594)	(0.070)							(0.960)	(0.030*)					
Accruals	6	0.8452	-0.6917	-0.6798	0.0969	0.0959	0.0117	-0.449	6	0.2221	-0.1408	-0.4267	0.0032	-0.0411	0.1256	-0.2671
		(0.045*)	(0.158)	(0.166)	(0.844)	(0.845)	(0.981)	(0.277)		(0.303)	(0.565)	(0.079)	(0.990)	(0.866)	(0.608)	(0.206)

tions present in popular music, becomes impounded into stock-market prices. Cross-sectionally, stocks that are more sensitive to investor sentiment will face a larger positive demand shock, and hence a larger increase in price, with lower expected returns in the future. However, existing theory does not give clear guidance as to the horizon length over which the decrease should be expected to materialize. This aspect of the negative relationship between investor sentiment and future returns remains an empirical question.

Table 9 shows that the immediate effect of orthogonalized music sentiment unwinds (on average) in the following month for CF/P and E/P, in the second month for OP, followed by Inv in the third month, and finally ME in the fifth month. We interpret this reversion pattern as reflecting the resilience of investor sentiment's influence on beliefs pertaining to different financial characteristics. For financial characteristics that closely track the firm's operations — e.g. cash flows and earnings — information is updated regularly and will reflect variability in operating performance. For this category of financial characteristics, new information emerges relatively frequently to confront and update investors' sentiment-driven initial beliefs. For slow-moving financial characteristics — e.g. investment style and capitalization level — investors may update beliefs less frequently, leading investor sentiment to have a longer-lasting effect.

For long-short portfolios sorted by ME and Inv, the regressions yield significant negative and positive parameter estimates. For instance, the results for $SFPC\text{-}M$ in explaining ME-based trading returns show that a one-unit increase[23] in music-sentiment will on average lead to a 60.4 basis-point decrease in the return five months later, and a 47.9 basis-point increase in the return six months later. Similarly, the results for $SFPC\text{-}M^{\perp}$ in explaining Inv-based trading returns show that a one-standard-deviation increase in music-sentiment will on average lead to a 31.2 basis-point decrease in the return three months later, and a 27.6 basis-point increase in the return four months later. This indicates that it is possible for the cross-sectional effect of sentiment to follow an overshoot-and-revert pattern over consecutive months. Combined with the

[23] $SFPC\text{-}M$ is not standardized, whereas $SFPC\text{-}M^{\perp}$ is standardized.

time-lag evidence discussed above, the present finding reinforces the view that price re-discovery following sentiment shocks is neither automatic nor direct.

7 Conclusion

In this paper we make use of unconventional (big) data and natural-language processing to develop a new sentiment indicator. Popular music's status as a pervasive carrier of emotional contagion serves as the premise for our focus. We extract a first-principal-component indicator from musical-composition attributes and lyrics-derived basic-emotion metrics. The resulting composite indicator performs well in predicting, or respectively explaining, stock returns both in time-series and cross-sectional analysis, both within-sample and out-of-sample, as well as in comparison to existing, widely used conventional sentiment-indicator benchmarks. Consistently across these empirical models, results reveal that the $SFPC\text{-}M$ composite indicator comprises signal plus noise. In part, the music-sentiment indicator reflects beliefs about fundamentals, which in turn yield positive predictive power for market returns at horizons of 12 months and above. Yet the music-sentiment indicator also captures emotion that is orthogonal to fundamentals. Orthogonalized music sentiment $SFPC\text{-}M^{\perp}$ predicts reductions in market returns over short horizons. We conclude that orthogonalized music sentiment captures pure noise from an economic standpoint, but that the statistically significant negative one-month-ahead parameter estimates in both the time-series and cross-sectional models are consistent with noise trading. Both within- and out-of-sample, our music-sentiment indicator is non-redundant given existing conventional sentiment indicators, and the best statistical models retain both indicators. Music sentiment complements, rather than replaces, existing sentiment indicators.

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