Music Sentiment and Stock Returns Around the World*

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Abstract

This paper introduces a real-time, continuous measure of national sentiment that is language-free and thus comparable globally: the positivity of songs that individuals choose to listen to. This is a direct measure of mood that does not pre-specify certain mood-affecting events nor assume the extent of their impact on investors. We validate our music-based sentiment measure by correlating it with mood swings induced by seasonal factors, weather conditions, and COVID-related restrictions. We find that music sentiment is positively correlated with same-week equity market returns and negatively correlated with next-week returns, consistent with sentiment-induced temporary mispricing. Results also hold under a daily analysis and are stronger when trading restrictions limit arbitrage. Music sentiment also predicts increases in net mutual fund flows, and absolute sentiment precedes a rise in stock market volatility. It is negatively associated with government bond returns, consistent with a flight to safety.

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The behavioral finance literature shows that investor sentiment significantly affects stock returns, in contradiction to the efficient market hypothesis. This literature has pioneered a range of sentiment measures that share a common theme – they specify an exogenous shock to a country's mood, such as international sporting results, aviation disasters, or the weather, and assume it affects the sentiment of the marginal investor.

In this paper, we take a different approach. Rather than studying shocks to sentiment, we seek a proxy for a country's *actual* sentiment.[1] Actual sentiment may be driven by a variety of factors and thus does not require us to pre-specify one particular driver. In addition, actual sentiment aims to capture the extent to which events affect investor mood. A country may have lost a soccer match, but the effect on mood is muted because the loss was predictable or soccer is not popular in that country. Thus, rather than using an exogenous shock that is assumed to affect national mood, we seek an endogenous measure that reflects it. We wish this measure to be available at a high frequency, at a country rather than city level, and globally comparable. This final requirement means that we desire a proxy that is language-free and thus does not require a sentiment dictionary, the accuracy of which may vary across languages.

While feelings are unobservable, they manifest in observable actions. However, no exists dataset on the vast majority of actions that reflect people's mood, such as aggressive behavior or language. We thus study the sentiment of songs that a country's citizens listen to. This idea is based on research from the psychology literature that individuals reflect their mood in their music choices. A range of studies document "emotion congruity", that music is used to validate emotion. For example, North and Hargreaves (1996) show that participants' preference for music matches their current emotional states. Saarikallio and Erkkilä (2007) document that unhappy subjects listen to sad music to express their emotions or attain closure,

[1] We use the terms "sentiment" and "mood" interchangeably in this paper. Other authors use "sentiment" as a broader term that captures not only mood, but also changes in beliefs or preferences from non-mood factors such as investor attention (e.g., Hirshleifer, Jiang, and DiGiovanni, 2020).

and Hunter, Schellenberg, and Griffith (2011) find that the typical preference for upbeat music is eliminated after inducing a downbeat mood.[2] Prior research has also shown that music sentiment is correlated with economic behavior or beliefs that may drive behavior. For example, Zullow (1991) shows that the optimism of the US top-40 songs forecasts GNP growth and Sabouni (2018) finds that the positivity of streamed music predicts the Michigan Consumer Sentiment Index.

Listening data are available on a large scale from Spotify, the leading online music platform worldwide. It had 365 million monthly active users as of June 2020, ensuring that music played on the platform reflects the mood of a sizeable share of a country's population. Based on Q4-2017 U.S. data, 74% of Spotify users were above 24 years old, and more than 30% were above 45.[3] Hence, financial market participants are likely to be represented in the sample of Spotify users. Spotify provides daily statistics of the top-200 songs by the total number of streams in a particular country. It also has an algorithm that classifies a song's *valence*, or positivity, trained on ratings of positivity by musical experts. We use the valence of the daily top-200 songs played on Spotify in 40 countries as a measure of the mood of its citizens.

Using an endogenous measure of sentiment also has potential disadvantages. The main concern is that people may listen to songs to attenuate rather than reflect their mood – for example, combat negative sentiment by playing an upbeat song. Such a concern is inconsistent with the above research on emotion congruity; for example, funerals play sad songs to reflect the mood rather than happy songs to affect it. To address this concern directly, we provide a

[2] As additional evidence, Cantor and Zillman (1973) induce emotions in subjects by showing them films and find that they then prefer emotionally congruent music. Chen, Zhou, and Bryant (2007) find that the desire to listen to sad music is strongest immediately after experiencing a negative mood; they are only likely to listen to uplifting music when some time has passed. Van den Tol and Edwards (2013) find that people listen to sad music after experiencing negative circumstances due to feeling connected with the music.

[3] Source: https://www.businessofapps.com/data/spotify-statistics/.

validation test using established mood proxies. First, we build on prior literature to identify seasonal factors likely to affect individuals' moods (e.g., Thaler, 1987; Kamstra et al., 2017; Birru, 2018; Hirshleifer, Jiang, and DiGiovanni, 2020). We find that periods of declining mood (e.g., September to October in the Northern Hemisphere) are associated with a significant decrease in our music-based sentiment measure. Second, prior literature documents evidence that cloud cover dampens investor mood (e.g., Hirshleifer and Shumway, 2003; Goetzmann et al., 2015); we find it is similarly associated with music sentiment. Third, the stringency of a government's restrictions imposed in response to COVID-19 negatively affects citizens' mood (e.g., Terry, Parsons-Smith, and Terry, 2020; Bueno-Notivol et al., 2021). We show that an increase in this stringency is associated with a decrease in music sentiment.

Our main analyses investigate the relation between music sentiment and stock market returns. We find a positive and significant association between music sentiment and contemporaneous returns, controlling for past returns, the world market return, seasonalities, weather conditions, and macroeconomic variables. A one-standard-deviation increase in music sentiment is associated with a higher weekly return of 8.1 basis points (bps), or 4.3% annualized. This effect reverses over the next week: a one-standard-deviation increase in music sentiment predicts a lower next-week return of 7.0 bps or -3.7% annualized. Both results are consistent with sentiment-induced temporary mispricing, and prior theoretical and empirical findings that negative investor sentiment causes prices to temporarily fall but subsequently correct (De Long et al., 1990; Baker and Wurgler, 2006, 2007; Edmans, Garcia, and Norli, 2007; Ben-Rephael, Kandel, and Wohl, 2012).

We obtain similar results with a daily analysis – music sentiment is associated with significantly higher contemporaneous stock returns, which subsequently reverse. Our results hold for both dollar and local currency returns, when excluding one country at a time to ensure that they are not driven by a specific country, and when excluding the 50 most-streamed songs per country to address the concern that Spotify suggests songs to users.

To further test whether sentiment is driving our results, we perform a series of additional analyses. First, the impact of sentiment should be stronger when limits to arbitrage are higher (Baker and Wurgler, 2006, 2007). Over our sample period, some countries implemented trading restrictions such as short-sale bans at the beginning of the COVID-19 pandemic, limiting arbitrage opportunities. We conduct difference-in-differences analyses around these plausibly exogenous shocks and find that the effect of sentiment on current and future returns intensifies.

Second, prior theoretical and empirical literature suggests that investor sentiment and the resulting noise trading can affect the volatility as well as level of asset prices (e.g., Black, 1986; De Long et al., 1990; Da, Engelberg, and Gao, 2015). We indeed find a significant contemporaneous correlation between absolute music sentiment and stock market volatility.

Third, as out-of-sample tests, we move from studying equity indices to equity mutual funds and government bond indices. Prior literature shows that mutual fund flows are affected by investor sentiment (e.g., Ben-Rephael, Kandel, and Wohl, 2011, 2012). We indeed find that music sentiment is significantly and positively associated with net equity fund flows. By contrast, it is significantly negatively associated with government bond index returns, consistent with a "flight to safety" (see also Baker and Wurgler, 2012; Laborda and Olmo, 2014; Da, Engelberg, and Gao, 2015).

Our study contributes to the literature on the effect of investor sentiment on the stock market. Prior studies have introduced a range of sentiment measures, each with their unique strengths but also some limitations. Some studies use rare events that capture sudden changes to investor mood, such as international sporting results (Edmans, Garcia, and Norli, 2007), aviation disasters (Kaplanski and Levy, 2010), terrorist attacks (Chen et al., 2020), and clock changes (Kamstra, Kramer, and Levi, 2000). Although powerful where available, such sentiment measures do not exist for most of the year. In addition, because they are discrete, they show that shocks to sentiment affect asset prices but do not have implications for more moderate changes. Weather variables such as cloud cover (Hirshleifer and Shumway, 2003; Goetzmann et al., 2015) or daylight hours (Kamstra, Kramer, and Levi, 2003) also represent exogenous shocks to sentiment. These measures are both continuous and available at a high frequency but do not capture the strength of their effect on investor mood; in addition, weather in the city where the national stock exchange is located may not be shared by the rest of the country.

Other papers, like ours, use endogenous measures of sentiment. Baker and Wurgler (2006) develop a sentiment index of market-based measures such as trading volume, the closed-end fund discount, initial public offering first-day returns and volumes, option-implied volatilities, and mutual fund flows. However, these factors could reflect economic fundamentals rather than sentiment; for example, implied volatility could be high due to uncertainty rather than irrationality. Brown and Cliff (2005) and Lemmon and Portniaguina (2006) use consumer sentiment surveys, but these are available at a low frequency, inquire about behavior rather than directly capturing behavior, and may not be filled in truthfully or carefully.

Da, Engelberg, and Gao (2015) use textual analysis of internet searches to develop a measure of negative sentiment, and find that it is correlated with market returns, volatility, and fund flows in the U.S.[4] Gao, Rhen, and Zhang (2020) expand this index to include non-finance

[4] Other papers using textual analysis to construct a sentiment measure include Tetlock (2007), Das and Chen (2007), Bollen, Mao, and Zeng (2011), and Garcia (2013). Sabouni (2018) and Kaivanto and Zhang (2019), like us, study music but only consider one and two countries, respectively. Their sentiment measure includes the song's lyrics. In addition to the issues with textual analysis, songs with positive music may have negative lyrics (e.g., "Pumped Up Kicks," "Born in the USA," "Good Riddance (Time Of Your Life)," and "Semi-Charmed Life").

terms and capture positive as well as negative sentiment, and link it with country-level returns across 38 countries. Like us, Gao, Rhen, and Zhang (2020) study an endogenous high-frequency measure of investor sentiment available globally. However, textual analysis requires pre-specifying a set of keywords as being positive or negative. The accuracy of this set may vary across languages, reducing global comparability. Loughran and McDonald (2016) review other challenges with textual analysis, such as disambiguating sentences, which likely also vary across languages.

Our music-based sentiment measure also involves subjectivity, since the valence algorithm was initially trained based on experts' opinion. However, the sentiment measure applies to songs all over the world, which increases comparability. While equivalent words in different languages have different meanings, music is less equivocal: as is often emphasized, "music is a universal language." Mehr et al. (2019) study 315 cultures and find that they use similar kinds of music in a similar context, suggesting music has universal properties that likely reflect commonalities of human cognition throughout the world. Thus, a measure of song valence is likely to be applicable globally. Moreover, music captures ineffable emotions that a word-based sentiment measure cannot.

Another difference is that search behavior may arise from information acquisition rather than reflecting sentiment. Someone may search for "unemployment" not out of concerns for his job, but to become informed about the economy. In contrast, music listening is primarily a consumption decision. Our approach thus infers individuals' sentiment from their consumption decisions. For most goods, national consumption data is unavailable at high frequency, and it is difficult to classify their purchase as resulting from positive or negative mood. In contrast, music consumption is available daily, and we can assess the valence of each song.

This paper is also related to studies investigating high-frequency proxies of sentiment using non-textual sources. Obaid and Pukthuanthong (2021) estimate sentiment in the U.S.

through a sample of editorial news photos. Like them, we study a measure that may convey sentiment more effectively than words, but an audio rather than visual one. Our analysis also differs by considering an endogenous measure of mood, studying 40 countries, and analyzing equity fund flows and government bond returns in addition to stock returns.

Finally, our study is part of a new stream of literature using big data in finance. Music sentiment satisfies the three features of big data identified by Goldstein, Spatt, and Ye (2021). It is large in size, aggregating the listening behavior across all Spotify listeners with a country every day. It is high dimension, as a song has multiple characteristics that feed into its valence measure. It is also unstructured, requiring an algorithm to assess its positivity. All three features mean that music streaming is an aggregate measure of consumption available at high frequency, whose positivity can be assessed to form a proxy for national sentiment.

This paper substantially expands and updates a preliminary paper by Fernandez-Perez, Garel, and Indriawan (2020) that correlates weekly music sentiment and stock returns in the U.S. Because the music sentiment measure is only available for a short time series, our cross section of 40 countries is particularly important to verify the robustness of its impact on stock returns, as well as to provide an "out-of-sample" test to address concerns of spurious correlation and data mining. Because music sentiment is language free and based on universal features of music, it is well suited to a global analysis. We study the impact of sentiment on volatility, mutual fund flows, and government bond indices, also helping to ensure out-of-sample validity and greater generalizability.

The rest of the paper is organized as follows. In Section 1, we discuss and validate the music sentiment measure. Section 2 reports our main results, and Section 3 presents additional analyses. Section 4 concludes.

1. Data and Variable Measurement

1.1 Music sentiment

To measure music sentiment, we collect data from Spotify.[5] Starting from January 1, 2017, Spotify has released, per country, daily statistics of the top-200 songs by the total number of streams.[6] A stream is counted in Spotify only once a song is played for at least 30 seconds; thus, if is a user "passively" listens to a song because it is suggested by Spotify or part of a playlist but promptly skips it, it is not in our data. As of December 2020, Spotify provides data for 70 countries. We only select countries where Spotify data are available since January 1, 2017, and MSCI stock market indices are available from Refinitiv (formerly Thomson Reuters). This procedure results in a total sample of 40 countries over the sample period from January 1, 2017, to December 31, 2020.[7] We identify over 58,000 unique songs with over 500 billion streams. On average, we have 8.6 million streams daily per country, with around 43,000 streams per song.

In addition to the top-200 songs, Spotify also provides a metric of a song's musical positivity known as *valence*. This metric is measured by Spotify's music intelligence division, The Echo Nest, which was initially a research spin-off from the MIT Media Lab and then acquired by Spotify in 2014. The Echo Nest assigned positivity scores to a sample of 5,000 songs, and then used machine learning to create an algorithm that is then applied to the rest of

[5] Readers and seminar audiences have suggested additional measures of mood sentiment to supplement the Spotify data, but none seem suitable. Record sales are less suitable because they are partly driven by a new record becoming available (e.g., if it is by an artist the purchaser likes) rather than sentiment; in addition, most current music consumption occurs through streaming rather than purchases. Ticket sales similarly are driven by when tickets are released (because popular concerts often sell out) rather than sentiment. Airplay is driven by the choice of the radio station, rather than an active listening choice by the individual; it is also constrained by the type of music the radio station typically airs.

[6] This information is released at https://spotifycharts.com/regional.

[7] We drop Andorra, Bulgaria, Cyprus, Egypt, Estonia, India, Israel, Lithuania, Luxembourg, Morocco, Romania, Russia, Saudi Arabia, South Africa, South Korea, Thailand, Ukraine, United Arab Emirates, and Vietnam because their Spotify data are only available for less than one year. We also drop Bolivia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Nicaragua, Paraguay, Slovakia, and Uruguay due to unavailability of MSCI stock market data.

the music in the world. Valence measures the positivity of the music, not the lyrics, avoiding the aforementioned concerns with textual analysis. It ranges from 0 to 1; songs with high valence sound more positive (e.g., happy, cheerful, euphoric), whereas songs with low valence sound more negative (e.g., sad, depressed, angry). Table A1 reports the songs with the highest and lowest valence per country in our sample period, and Table A2 does so for Billboard's Top 100 songs of the 2010s.[8]

We construct a stream-weighted average valence (henceforth *SWAV*) across the top-200 songs for each day *d* and country *i* as follows:

$$SWAV_{i,d} = \sum_{j=1}^{200}\left(\frac{Streams_{j,i,d}}{\sum_{j=1}^{j=200} Streams_{j,i,d}} \cdot Valence_{j,i,d}\right) \tag{1a}$$

where $Streams_{j,i,d}$ is the total streams for song *j* of country *i* on day *d*, and $Valence_{j,i,d}$ is the valence of the song *j* of country *i* on day *d.*

Fig. 1 shows a chart of the full sample average *SWAV* across countries. We observe that South American countries have a higher average *SWAV*, whereas Asian countries have a lower average *SWAV*. Fig. 2 plots daily *SWAV* over time for three countries: US, Brazil (which has one of the highest average *SWAV*), and Taiwan (which has one of the lowest). Although *SWAV* is persistent, it also exhibits variations over time that we can exploit to construct a music-based sentiment measure. The coefficient of variation (standard deviation divided by the mean) of daily *SWAV* is 5.5% when computed separately for each country and then averaged. The persistence of *SWAV* means that our music-based sentiment measure is based on changes in *SWAV*.

Insert Figure 1 & 2 here

[8] This list is available at https://www.billboard.com/charts/decade-end/hot-100.

To match our music sentiment measure with stock market and macroeconomic data, we aggregate it at a weekly level to avoid non-synchronicity between the opening and closing times of the stock markets and the time of day that Spotify reports its daily statistics. Such non-synchronicity would lead to a daily measure of *SWAV* partially leading daily stock returns for some indices and lagging it for others. We define our sentiment measure as the weekly change in sentiment, both to control for country-level differences in the average level of sentiment, as shown in Figure 1, and also because we expect the change in sentiment to cause changes in stock prices. Our music-based mood proxy, *Music Sentiment*, is thus given by:

$$Music\ Sentiment_{i,t} = SWAV_{i,t} - SWAV_{i,t-1}, \tag{1b}$$

where $SWAV_{i,t}$ is the stream-weighted average valence for week *t* (taken every Friday). *Music Sentiment* is thus the total change in the stream-weighted average valence of the top-200 songs citizens of country *i* listen to in week *t*.

1.2 Sample and summary statistics

We obtain country-level MSCI total return indices from Refinitiv. We use dollar returns, consistent with the literature on international asset pricing (e.g., Griffin, 2002; Fama and French, 2017). The list of indices used for each country is given in Table A3 in the Appendix. Table 1 provides summary statistics by country on our music-based sentiment measure, market index returns, and volatility. We winsorize all continuous variables in our study at the 2.5% and 97.5% levels, similar to Da, Engelberg, and Gao (2015). *Music Sentiment* ranges from -0.024% (Turkey) to 0.109% (Latvia). Weekly average stock market returns range from -0.009% (Turkey) to 0.449% (Taiwan), and weekly average stock market volatility ranges from 0.648% (Malaysia) to 2.060% (Argentina). The average autocorrelation for *Music Sentiment* is -0.19.

Insert Table 1 here

1.3 Validation of our music-based sentiment measure

We begin our empirical analysis by validating our music-based sentiment measure using variables that prior research has shown to affect mood and that are also available for our sample countries. We first draw on prior literature to identify seasonal factors likely to affect individuals' moods (e.g., Thaler, 1987; Kamstra et al. 2017; Birru, 2018; Hirshleifer, Jiang, and DiGiovanni, 2020). January is associated with the improving mood of the New Year period. For Northern Hemisphere countries, March is associated with the highest recovery from seasonal affective disorder (SAD). By contrast, the months of September and October are associated with the highest onset of the SAD effect. Kamstra et al. (2003) show that the SAD effect is also observed in the Southern Hemisphere, but six months out of phase.

Another strand of papers relates mood to weather conditions. Prior literature finds that cloud cover affects mood (see, e.g., Hirshleifer and Shumway, 2003; Goetzmann et al., 2015). We test whether our music sentiment is related to weather conditions. We collect local climatological data from the National Oceanic and Atmospheric Administration website, which contains hourly weather observations from over 20,000 weather stations worldwide. For each weather station, we can observe the degree of cloud cover, which takes on integer values from 0 (clear sky) to 8 (overcast sky). Following Goetzmann et al. (2015), the average daily cloud cover is calculated per country using hourly values from 6am to 12pm across the country's various weather stations.[9] Because daily cloud cover is highly seasonal, we deseasonalize it by subtracting each week's mean cloudiness from the time-series mean, similar to Hirshleifer and Shumway (2003). We call this measure deseasonalized cloud cover (*DCC*). Because our sentiment measure captures a change in sentiment, we use the average daily change in

[9] Goetzmann et al. (2015) explain that the 6am to 12pm window is when investors are most likely to observe outdoor weather conditions. For robustness, we also calculate the average daily cloud cover from 6am to 4pm, similar to Hirshleifer and Shumway (2003). The results are qualitatively similar.

deseasonalized cloud cover within a week in our validation test ($\overline{\Delta DCC}$).[10] We use weather-induced and calendar-related mood swings rather than events such as international sports results or aviation disasters, due to few such events in our sample period.

Finally, we expect music-based sentiment to be lower when the government imposes stronger restrictions in response to COVID-19. Recent studies show that such restrictions have adversely affected citizens' mood (e.g., Terry, Parsons-Smith, and Terry, 2020; Bueno-Notivol et al., 2021). We compile an index based on lockdown restrictions compiled by the University of Oxford's COVID-19 government response tracker.[11] These include school closures, workplace closures, cancellations of public events, restrictions on gathering sizes, closures of public transport, stay-at-home requirements, restrictions on internal movement, and restrictions on international travel. (We do not include other government responses contained in the tracker, such as vaccination requirements and testing policy, that do not lead to closures or containment). Our index commences on January 1, 2020.

To validate our music construct as a proxy for mood, we test how it relates to the above seasonal mood patterns, weather conditions, and COVID restrictions. More specifically, we estimate the following panel regression:

$$Music\ Sentiment_{i,t} = \alpha + \beta_1 \cdot Positive\ Months_{i,t} + \beta_2 \cdot Negative\ Months_{i,t}$$

$$+\beta_3 \cdot \overline{\Delta DCC}_{i,t} + \beta_4 \cdot \Delta COVID_{i,t} + \varepsilon_{i,t} \quad (2)$$

where $Positive\ Months$ is an indicator variable that equals 1 for January and March for Northern Hemisphere countries (January and September for Southern Hemisphere countries – we do not shift January because it remains the New Year in the Southern Hemisphere) and 0 otherwise, $Negative\ Months$ is an indicator variable that equals 1 in September and October

[10] Hirshleifer and Shumway (2003) show that both the change and level of cloudiness are related to mispricing.
[11] These data are available from https://data.humdata.org/dataset/oxford-covid-19-government-response-tracker.

for Northern Hemisphere countries (March and April for Southern Hemisphere countries) and 0 otherwise[12], $\overline{\Delta DCC_{i,t}}$ is the average daily change in deseasonalized cloud cover within week t, and $\Delta COVID_{i,t}$ is the weekly change in the stringency of a government's response to COVID. We estimate Eq. (2) using ordinary least squares (OLS) and report White-corrected *t*-statistics, which are robust to heteroscedasticity. Table A4 lists the variable definitions and sources.

Table 2 reports the regression estimates. Column (1) includes the month dummies and country and year fixed effects. It shows that decreasing mood periods (*Negative Months*) are significantly negatively associated with music-based sentiment, with a *t*-statistic exceeding 9; we find no significant effect in increasing mood periods (*Positive Months*). Column (2) includes the change in cloudiness and country and month fixed effects and shows that an increase in cloudiness is associated with a significant decrease in music sentiment (at the 1% level). Column (3) shows that more stringent lockdown restrictions are associated with a decrease in music sentiment at the 5% level. Column (4) includes all of the above explanatory variables together and shows that the aforementioned associations hold. These results suggest that our music-based sentiment measure captures mood swings of a country's individuals caused by well-established mood-affecting factors.[13] The stronger results for decreasing mood periods are consistent with prior research that negative sentiment has greater effects than positive sentiment (e.g., Edmans, Garcia, and Norli, 2007).

Insert Table 2 here

[12] Kamstra et al. (2003) find that the effect of SAD is more pronounced in higher-latitude countries. Therefore, we consider only mid-latitude countries (N23º26'22" - N66º33'39" in the Northern hemisphere and S23º26'22" - S66º33'39" in the Southern hemisphere) where the four seasons are clearly distinguished. The results are similar if we consider all countries.

[13] Table A5 confirms the results of Table 2 at a daily frequency. Specifically, music sentiment is lower on decreasing-mood days (Monday and Sunday) and higher on increasing-mood days (Friday and Saturday), consistent with the evidence reviewed by Birru (2018) that also finds a link between sentiment and the day of the week. In addition, the daily increase in cloud cover remains negatively associated with music sentiment.

2. Results

2.1 Music sentiment and stock market returns

In our main analysis, we investigate the relation between music sentiment and stock market returns. We estimate the following baseline panel regression:

$$RET_{i,t} = \alpha + \beta_1 \cdot Music\ Sentiment_{i,t} + \sum \Gamma \cdot Controls_{i,t} + \varepsilon_{i,t}, \qquad (3)$$

where $RET_{i,t}$ is the weekly return of the country's stock market index, and $Controls_{i,t}$ is a vector of control variables. We control for the one-week-lagged market return to address autocorrelation, and the change in cloud cover ($\overline{\Delta DCC}$), because it is correlated with both music sentiment (as shown in Table 2) and stock returns (Hirshleifer and Shumway, 2003). If sentiment affects domestic stock returns, it should do so over and above the effect of global events. Thus, we include the contemporaneous weekly world return (*World RET)* and three macroeconomic variables. Because macroeconomic variables are unavailable at high frequency for non-U.S. countries, we employ U.S. variables as in Gao, Rhen, and Zhang (2020); relatedly, Brusa, Savor, and Wilson (2020) show that U.S. macroeconomic policy has a larger effect on foreign country stock markets than local macroeconomic policy.

Specifically, we control for the weekly change in uncertainty related to economic policies, using the weekly news-based measure of U.S. economic policy uncertainty (*ΔEPU*) developed by Baker, Bloom, and Davis (2016) and taken from Scott Baker's website.[14] We also control for the weekly change in U.S. macroeconomic activity using the Aruoba, Diebold, and Scotti (2009) index (*ΔADS*) from the Federal Reserve website.[15] Finally, we control for the

[14] This measure is constructed by counting the number of U.S. newspaper articles achieved by the NewsBank Access World News database with at least one term from each of the following three categories: (i) "economic" or "economy"; (ii) "uncertain" or "uncertainty"; and (iii) "legislation," "deficit," "regulation," "congress," "Federal Reserve," or "White House." Baker, Bloom, and Davis (2016) provide evidence that EPU captures perceived economic policy uncertainty.
[15] This index extracts the latent state of macroeconomic activity from a large number of macroeconomic variables (jobless claims, payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales, and quarterly real gross domestic product) using a dynamic factor model.

implied volatility of the S&P 500 (*VIX*) (as in Baker and Wurgler, 2007; Da, Engelberg, and Gao, 2015), obtained from the Chicago Board Options Exchange website. It captures investors' expectations about the volatility of the U.S. stock market over the following 30 calendar days. For all regressions henceforth, we use country fixed effects to control for other cross-sectional differences that may drive stock returns and month fixed effects to control for seasonal mood swings not captured by our music-based sentiment measure.

Table 3, Panel A reports the estimation results of Eq. (3). We find a positive association between music sentiment and contemporaneous market returns. A one-standard-deviation increase in music sentiment is associated with a higher weekly return of 8.1 bps (4.3% annualized), significant at the 1% level. Panel B reports the estimation results of Eq. (3) using one-week-lagged music sentiment as the key independent variable and finds evidence of reversal. A one-standard-deviation increase in music sentiment is associated with a lower next-week return of 7.1 bps (-3.7% annualized), significant at the 1% level. In sum, music sentiment is positively correlated with same-week returns and negatively correlated with next-week returns, a price-reversal pattern consistent with sentiment-induced temporary mispricing.

Turning to the control variables, we observe a positive association between world and domestic market returns, significant at the 1% level. This finding suggests that domestic stock markets are highly integrated. Results also show that domestic market returns are serially correlated, positively related to increases in VIX, and negatively related to increases in economic policy uncertainty.

Insert Table 3 here

Table 4 reports the results of robustness tests. Panel A shows that the results in Table 3 are robust to including both contemporaneous and one-week-lagged music sentiment in the same regression. Both coefficients are statistically significant with the expected signs. Panel

B demonstrates that the results are robust to estimating Eq. (3) with local currency returns, to address the concern that sentiment affects the exchange rate.

Although Spotify mainly recommends music based on a user's listening activity and preferences, it also has a section called *Hot Hits*. This section contains the country's daily top-50 most popular songs, irrespective of the user's listening preferences. Users might be tempted to listen from this pool of songs. Because individuals are not forced to follow these recommendations, and a song does not enter our data unless it is listened to for at least 30 seconds, passively listening to *Hot Hits* is unlikely to affect our measure. Nevertheless, we examine whether our results are robust to excluding recommended songs. Because Spotify does not provide historical data on the *Hot Hits*, we assume they are the 50 most-streamed songs in our top-200. If we exclude these songs from our *SWAV* calculation and calculate the correlation between this new measure and the measure based on all 200 songs, we find an average correlation of 0.6 across countries. Based on this new *SWAV*, we reconstruct our music sentiment and re-estimate Eq. (3). Panel C reports the results. The results remain significant at the 1% level in all specifications. The point estimates are slightly smaller because we are removing popular songs that may have been chosen even if not recommended.

In our main specification, we included month-of-the-year fixed effects to control for seasonal mood swings. We did not control for year-month fixed effects since music sentiment varies from year-month to year-month; doing so would limit our identification to comparing weekly stock returns within a given month. We thus instead capture time-varying global drivers of stock market returns by controlling for world returns, ΔEPU, ΔADS, and *VIX*. Because these variables may not fully reflect time-varying drivers of returns, Panel D tests the robustness of our findings to the inclusion of year-month fixed effects and shows that the inferences are unchanged.

Panel E reports the results of Table 3 when we exclude one country at a time from our sample. It shows our main results are not driven by a specific country. In unreported results, we also find our results are robust to excluding world returns from our set of control variables, alleviating the concern that some country indices represent a significant portion of the world index.

Insert Table 4 here

Our main analysis focuses on contemporaneous weekly returns because of the non-synchronicity between the valence of songs streamed on Spotify and stock market returns. However, one potential concern with a contemporaneous analysis is reverse causality. For example, negative stock returns might induce a low mood and cause people to listen to negative songs. As a result, the association between music sentiment and stock market returns at a weekly frequency could result from positive (negative) market returns at the start of the week, inducing a positive (negative) mood later in the week.

Table 5 thus studies the link between daily music sentiment and daily stock returns. We expect a positive association between music sentiment and stock market returns and a subsequent reversal in the following days. Because days in Spotify are based on the UTC time zone, and some markets may have earlier or later time zones, we measure contemporaneous music sentiment as the average sentiment over the current day and the one day prior. As controls, we include four additional lags of music sentiment (from days *d-2* to *d-5*), the change in cloud cover, and the domestic market returns. We include contemporaneous, next-day, and prior-day world market returns, as in Edmans, Garcia, and Norli (2007), because some markets may be lagging while others may be leading the world index. For similar reasons, we include daily leads and lags for the U.S. macroeconomic variables. In addition to country and month fixed effects, we include day-of-the-week fixed effects, because Table A5 shows they are significantly correlated with music sentiment.

Insert Table 5 here

We find that daily index returns are positively correlated with contemporaneous music sentiment and negatively correlated with sentiment five days prior, suggestive of a reversal. Both coefficients are significant at the 5% and 1% levels, respectively. In economic terms, based on column (6), a one-standard-deviation increase in contemporaneous music sentiment is associated with a higher return of 1.2 bps (3.0% annualized); a one-standard-deviation increase in music sentiment five days prior is associated with a lower return of 1.0 bps (-2.4% annualized). This result is consistent with the pattern we observe at the weekly frequency and suggests that mood swings, as reflected in music sentiment, lead to changes in stock prices.

That it takes several days for the reversal to manifest is consistent with prior research on the effect of sentiment on the stock market. For example, Tetlock (2007), Kaplanski and Levy (2010), and Obaid and Pukthuanthong (2021) find that no reversal occurs until day 3. These papers study the U.S., which has fewer trading frictions than our global sample; as a result, mispricing may be corrected faster. In unreported analyses, we find that in our setting, the reversal also occurs on day 3 for the U.S.

3. Additional Analyses

3.1. Limits to arbitrage

3.1.1. Trading restrictions

Several factors can exacerbate the effect of investor sentiment on asset prices. One of the most salient ones is limits to arbitrage (Pontiff, 1996; Shleifer and Vishny, 1997; Baker and Wurgler, 2006). We thus conduct difference-in-differences analyses around plausibly exogenous shocks to limits to arbitrage. Specifically, we exploit the introduction of trading restrictions in some of our sample countries during the COVID-19 pandemic as a shock that increased limits to arbitrage. The main trading restriction studied by prior research is a short-sale ban. For example, Ofek, Richardson, and Whitelaw (2004) find that short-sale restrictions lead to greater deviations from put-call parity in options markets. Bris, Goetzmann, and Zhu (2007) document that prices incorporate negative information faster in countries where short sales are allowed and practiced. Gao, Rhen, and Zhang (2020) show the effect of sentiment is stronger in countries with short-selling bans during the global financial crisis.

Table A6 lists the countries that introduced short-selling bans during the COVID-19 pandemic, as well as the start and end dates of the short-selling bans from the Yale Program on Financial Stability. For instance, in France, the Financial Market Authority announced a short-selling ban between March 17, 2020, and May 18, 2020, "in the light of the outbreak of the Coronavirus and its consequences on the economy and financial markets."[16] These bans were unexpected and country-specific; many countries exposed to COVID-19 did not introduce them. In addition to short-sale bans, another trading restriction is volume limits. During the pandemic, Australia limited the number of trades that can be executed each day, forcing high-volume investors to reduce their volumes and thus lowering their ability to correct mispricing.

We estimate the following difference-in-differences regression:

$$RET_{i,t} = \alpha + \beta_1 \cdot Music\ Sentiment_{i,t} + \beta_2 \cdot Music\ Sentiment_{i,t} \times BAN_{i,t} + \beta_3 \cdot BAN_{i,t} + \sum \Gamma \cdot Controls_{i,t} + \varepsilon_{i,t} \tag{4}$$

where *BAN* equals 1 if a country *i*'s stock market is subject to a trading restriction for the full week *t*, and 0 otherwise. We expect the stock price to be more responsive to changes in music

[16] http://www.amf-france.org/en/news-publications/news-releases/amf-news-releases/amf-announces-short-selling-ban-one-month.

sentiment when limits to arbitrage are greater, that is, for β_2 to be positive (negative) for current (lagged) music sentiment.

Panels A and B of Table 6 report the estimation results of Eq. (4) for current and one-week-lagged music sentiment, respectively. We find that the coefficient of the interaction term is significantly positive for current returns and significantly negative for future returns. Music sentiment is associated with greater contemporaneous stock returns and subsequent reversals under trading restrictions. Specifically, a one-standard-deviation increase in music sentiment is associated with a 33.6 bps greater increase in the contemporaneous return in ban weeks versus non-ban weeks and a 89.2 bps greater decrease in future returns.[17] In sum, the effect of music sentiment on market returns is markedly stronger when a country's stock market is subject to limits to arbitrage.

Insert Table 6 here

3.1.2. Small versus large stocks

While our first limit-to-arbitrage test relies on time variation in the shorting ability of investors, we now study cross-sectional differences in investors' ability to conduct arbitrage across stocks. Small stocks are particularly risky and costly to arbitrage; indeed, prior literature shows that the association between sentiment and stock market returns is stronger for smaller stocks (e.g., Baker and Wurgler, 2006; Edmans, Garcia, and Norli, 2007). Hence, we expect the effect of sentiment to be stronger in small stocks than in large stocks. To test our conjecture, for each country, we collect the time series of MSCI small- and large-cap indices from Refinitiv.[18] Then,

[17] Although the magnitude is large, we also find a similar magnitude when we control for the COVID-19 period, drop one country at a time, focus on countries implementing trading restrictions only, focus on EU countries because they are likely to have been exposed to COVID-19 to a similar degree, compare the association in post-ban months with the one in the same number of pre-ban months, and interact the ban dummy with the other control variables.

[18] MSCI provides small and large cap indices for all the countries in our sample except Iceland, Latvia, and Panama.

we estimate Eq. (3), replacing domestic market returns with small or large MSCI index returns as our main dependent variable.

Insert Table 7 here

Table 7 reports the estimation results. We find that music sentiment is positively and significantly correlated with both small- and large-cap index returns. However, the effect of music sentiment is greater for small stocks. A one-standard-deviation increase in music sentiment corresponds with a contemporaneous 8.9 bps per week (4.6% p.a.) increase, and a future -8.4 bps per week (-4.4% p.a.) decrease in large-cap index returns; the corresponding features for small-cap index returns are 12.86 bps per week (6.6% p.a.) and -10.1 bps per week (-5.2% p.a.). For a one-sided Wald test for equality in coefficients between large and small indices, the *p*-values are 0.078 for the contemporaneous regression and 0.263 for the lagged regression. Thus, our results only indicate weak evidence that the effect of sentiment is stronger for small stock indices.

3.2. Stock market volatility

Prior literature suggests that investor sentiment and the resulting noise trading can affect the volatility as well as level of asset prices (Black, 1986; De Long et al., 1990) because sentiment should cause prices to first deviate from fundamentals and then correct. Our results at a daily frequency already show that, within a week, music sentiment is first associated with an increase in stock market returns and then a reversal, consistent with sentiment exacerbating stock market return variations. To investigate this effect further, we study the relationship between weekly stock market volatility and contemporaneous weekly absolute music sentiment. We study absolute music sentiment, because large changes in sentiment in either direction should lead to more trading. We measure weekly volatility as the standard deviation of daily stock market returns within a week.

To test our conjecture, we estimate the following panel regression:

$$VOL_{i,t} = \alpha + \beta_1 \cdot \left|Music\ Sentiment_{i,t}\right| + \sum \Gamma \cdot Controls_{i,t} + \varepsilon_{i,t} \tag{5}$$

where *Controls* include the previous control variables, month and country fixed effects, and one-week-lagged stock market volatility. We exclude the VIX because our dependent variable is market volatility.

Table 8 reports the estimation results of Eq. (5). We document a strong contemporaneous correlation between absolute music sentiment and stock market volatility. A one-standard-deviation increase in absolute music sentiment is associated with a contemporaneous 3.7 bps increase in stock market volatility, which is 3.48% of the average weekly volatility of 1.06%. Our findings on stock market returns and stock market volatility paint a consistent picture of sentiment-induced stock price deviations from fundamentals.

Insert Table 8 here

3.3. Net equity fund flows

If sentiment affects investment decisions, we would expect it to influence trades of mutual funds, not just individual equities. For example, a positive mood should lead investors to be optimistic and thus buy into funds; indeed, Ben-Rephael, Kandel, and Wohl (2011, 2012) find that individual investor sentiment is significantly positively correlated with mutual fund flows.

We expect music sentiment to be positively related to mutual fund net inflows. We use both contemporaneous and one-week-lagged music sentiment because it takes several days for flows to be settled and reported (Da, Engelberg, and Gao, 2015). For stock indices, we predicted a negative relationship with lagged sentiment because arbitrageurs may subsequently undo temporary mispricing. However, no analogous concept exists of arbitrage undoing mutual fund inflows; combined with the delays in settling and reporting flows, we predict positive associations with both contemporaneous and lagged sentiment.

We collect information on daily net fund flows from Morningstar, focusing on open-end equity mutual funds denominated in local currency, and convert these flows to U.S. dollars. We remove duplicates (funds with the exact same time series of net flows and size) and funds with fewer than one observation per week on average (i.e., fewer than 188 observations over our sample period). We also drop funds that started after the beginning of our sample period (January 1, 2017) and fund-week observations with less than \$15 million of assets under management, following Pástor and Vorsatz (2020). The latter is because, for small funds, modest dollar flows can translate into extreme percentage flows; the results are similar when we use alternative cut-off points such as \$20 million of assets under management. This screening process results in 8,392 equity funds from 31 different countries and around 1,569,000 fund-week observations.[19]

For each fund, we aggregate the daily net fund flows within the week and scale the weekly net fund flows by the fund's total assets under management at the end of the previous week (e.g., Kamstra, Kramer, and Levi, 2017). We then estimate the following panel regression:

$$Net\ Flows_{f,i,t} = \alpha + \sum_{j=0}^{1} \beta_j \cdot Music\ Sentiment_{i,t-j} + \sum \Gamma \cdot Controls_{i,t} + \varepsilon_{f,i,t} \qquad (6)$$

where $Net\ Flows_{f,i,t}$ is the weekly scaled net flow of fund *f*, in country *i*, in week *t*. *Controls* are our previous controls, including month and fund fixed effects, plus one-week-lagged net

[19] The countries we exclude from our analysis as a result of our screening process are Argentina, Canada, Colombia, Hungary, Latvia, Panama, Peru, Poland, and Turkey.

equity fund flows to control for potential serial correlation in the fund flows. These controls are used in Da, Engelberg, and Gao (2015), for instance.

Table 9 reports the results of the estimation of Eq. (6). We find that both contemporaneous and one-week-lagged music sentiment are positively related to mutual fund flows, significant at the 1% level. A one-standard-deviation increase in music sentiment corresponds to an average increase in net fund flows of 0.3 bps the same week and 0.3 bps the following week. Based on the average fund size of $976 million, this increase corresponds to a weekly (annual) net flow of $29,000 ($1.5 million) the same week and $31,000 ($1.6 million) the following week.[20] The former is comparable with the average weekly net flow in our sample of -$78,714. Our results suggest that increases in music sentiment are associated with significant inflows to the equity market.

Insert Table 9 here

3.4. Government bonds

Prior literature suggests a "flight to safety," whereby investors move from risky to safe assets when their sentiment is low (e.g., Baker and Wurgler, 2012; Laborda and Olmo, 2014; Da, Engelberg, and Gao, 2015). Thus, we hypothesize that low sentiment not only leads investors to move out of equities (as shown in Table 3), but also to move into government bonds. We test this hypothesis by studying the returns of the Refinitiv Datastream Benchmark Government Bond Index. We use the returns of the five-year bond index because this maturity has the greatest data availability (Pitkäjärvi, Suominen, and Vaittinen, 2020).

Table 10 reports the results of the estimation of Eq. (3), replacing equity index returns with government bond index returns. For contemporaneous returns, we find the opposite result

[20] Wang and Young (2020) find that a one-standard-deviation increase in the level of terrorism corresponds to an average decline in fund inflows of $197,000 per month, or $45,500 per week. This order of magnitude is similar to our effect, although larger because terrorism likely has a larger effect than sentiment reflected in music.

for equity indices, that is, a negative and significant association between music sentiment and government bond index returns. In terms of economic significance, a one-standard-deviation increase in music sentiment is associated with a contemporaneous decrease in government bond returns of 0.01 bps per week, or -0.5% per year. This effect is economically large and represents more than 20% of the mean government bond returns of 2.2% per year. However, we find no relationship with future returns.

Insert Table 10 here

4. Conclusion

This study introduces a novel measure of investor sentiment, which captures actual sentiment rather than shocks to sentiment. It is continuous, available at a high frequency and on a global scale, and does not require the pre-specification of particular mood-affecting events or words that capture mood. We provide validation tests and show that seasonal factors, such as mood-decreasing months and increases in cloud cover, plus COVID-related restrictions, are associated with a significant decrease in our music-based sentiment measure.

Our main result is a positive and significant relation between music sentiment and contemporaneous market returns, controlling for world market returns, seasonalities, and macroeconomic variables. We also find a significant price reversal the following week. Taken together, our findings are consistent with sentiment-induced temporary mispricing that subsequently reverses.

We show that the relationship between music sentiment and market returns is stronger when countries implemented trading restrictions such as short-sale bans during the COVID-19 pandemic, consistent with greater limits to arbitrage. Music sentiment also predicts increases in net mutual fund flows and decreases in government bond returns, and absolute sentiment precedes a rise in stock market volatility. Overall, our study provides evidence that a proxy for the actual sentiment of a country's citizens is significantly correlated with asset prices.

References

Aruoba, S. B., Diebold, F. X., Scotti, C., 2009. Real-time measurement of business conditions. J. Bus. Econ. Stat. 27, 417–427.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Financ. 61, 1645–1680.

Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. J. Econ. Perspect. 21, 129–152.

Baker, M., Wurgler, J., 2012. Comovement and predictability relationships between bonds and the cross-section of stocks. Rev. Asset Pric. Stud. 2, 57–87.

Baker, S. R., Bloom, N., Davis, S. J., 2016. Measuring economic policy uncertainty. Q. J. Econ. 131, 1593–1636.

Ben-Rephael, A., Kandel, S., Wohl, A., 2011. The price pressure of aggregate mutual fund flows. J. Financial Quant. Anal. 46, 585–603.

Ben-Rephael, A., Kandel, S., Wohl, A., 2012. Measuring investor sentiment with mutual fund flows. J. Financ. Econ. 104, 363–382.

Birru, J., 2018. Day of the week and the cross-section of returns. J. Financ. Econ. 130, 182–214.

Black, F., 1986. Noise. J. Financ. 41, 529–543.

Bollen, J., Mao, H., Zeng, X., 2011. Twitter mood predicts the stock market. J. Comput. Sci. 2, 1–8.

Bris, A., Goetzmann, W. N., Zhu, N., 2007. Efficiency and the bear: Short sales and markets around the world. J. Financ. 62, 1029–1079.

Brown, G. W., Cliff, M. T., 2005. Investor sentiment and asset valuation. J. Bus. 78, 405–440.

Brusa, F., Savor, P., Wilson, M., 2020. One central bank to rule them all. Rev. Financ. 24, 263–304.

Bueno-Notivol, J., Gracia-García, P., Olaya, B., Lasheras, I., López-Antón, R., Santabárbara, J., 2021. Prevalence of depression during the COVID-19 outbreak: a meta-analysis of community-based studies. Int. J. Clin. Health Psychol. 21, 100196.

Cantor, J. R., Zillman, D., 1973. Resentment toward victimized protagonists and severity of misfortunes they suffer as factors in humor appreciation. J. Exp. Res. Pers. 6, 321–329.

Chen, Y., Goyal, A., Veeraraghavan, M., Zolotoy, L., 2020. Terrorist attacks, investor sentiment, and the pricing of initial public offerings. J. Corp. Financ. 65, 101780.

Chen, L., Zhou, S., Bryant, J., 2007. Temporal changes in mood repair through music consumption: Effects of mood, mood salience, and individual differences. Media Psychol. 9, 695–713.

Da, Z., Engelberg, J., Gao, P., 2015. The sum of all FEARS: Investor sentiment and asset prices. Rev. Financ. Stud. 28, 1–32.

Das, S. R., Chen, M. Y., 2007. Yahoo! for Amazon: Sentiment extraction from small talk on the web. Manage. Sci. 53, 1375–1388.

De Long, J. B., Shleifer, A., Summers, L. H., Waldmann, R. J., 1990. Noise trader risk in financial markets. J. Polit. Econ. 98, 703–738.

Edmans, A., Garcia, D., Norli, Ø., 2007. Sports sentiment and stock returns. J. Financ. 62, 1967–1998.

Fama, E. F., French, K. R., 2017. International Tests of a Five-Factor Asset Pricing Model. J. Financ. Econ. 123, 441–463.

Fernandez-Perez, A., Garel, A., Indriawan, I., 2020. Music sentiment and stock returns. Econ. Lett. 109260.

Garcia, D., 2013. Sentiment during recessions. J. Financ. 68, 1267–1300.

Gao, Z., Rhen, H., Zhang. B., 2020. Googling investor sentiment around the world. J. Financial Quant. Anal. 55, 549–580.

Goetzmann, W. N., Kim, D., Kumar, A., Wang, Q., 2015. Weather-induced mood, institutional investors, and stock returns. Rev. Financ. Stud. 28, 73–111.

Goldstein, I., Spatt, C. S., Ye., M., 2021. Big data in finance. Rev. Financ. Stud. 34, 3215–3225.

Griffin, J. M., 2002. Are the Fama and French factors global or country specific? Rev. Financ. Stud. 15, 783–803.

Hirshleifer, D., Shumway, T., 2003. Good day sunshine: Stock returns and the weather. J. Financ. 58, 1009–1032.

Hirshleifer, D., Jiang, D., DiGiovanni, Y. M., 2020. Mood beta and seasonalities in stock returns. J. Financ. Econ. 137, 272–295.

Hunter, P. G., Schellenberg, E. G., Griffith, A. T., 2011. Misery loves company: Mood-congruent emotional responding to music. Emotion 11, 1068.

Kaivanto, K., Zhang, P., 2019. Popular music, sentiment, and noise trading. Lancaster University. Unpublished working paper.

Kamstra, M. J., Kramer, L. A., Levi, M. D., 2000. Losing sleep at the market: The daylight saving anomaly. Am. Econ. Rev. 90, 1005–1011.

Kamstra, M. J., Kramer, L. A., Levi, M. D., 2003. Winter blues: A SAD stock market cycle. Am. Econ. Rev. 93, 324–343.

Kamstra, M. J., Kramer, L. A., Levi, M. D., Wermers, R., 2017. Seasonal asset allocation: Evidence from mutual fund flows. J. Financial Quant. Anal. 52, 71–109.

Kaplanski, G., Levy, H., 2010. Sentiment and stock prices: The case of aviation disasters. J. Financ. Econ. 95, 174–201.

Laborda, R., Olmo, J., 2014. Investor sentiment and bond risk premia. J. Financial Mark. 18, 206–233.

Lemmon, M., Portniaguina, E., 2006. Consumer confidence and asset prices: Some empirical evidence. Rev. Financ. Stud. 19, 1499–1529.

Loughran, T., McDonald, B., 2016. Textual analysis in accounting and finance: A survey. J. Account. Res. 54, 1187–1230.

Mehr, S. A., Singh, M., Knox, D., Ketter, D. M., Pickens-Jones, D., Atwood, S., ... Howard, R. M. 2019. Universality and diversity in human song. Science 366.

North, A. C., Hargreaves, D. J., 1996. Situational influences on reported musical preference. Psychomusicology: A Journal of Research in Music Cognition 15, 30–45.

Obaid, K., Pukthuanthong, K., 2021. A picture is worth a thousand words: Measuring investor sentiment by combining machine learning and photos from news. J. Financ. Econ.. forthcoming.

Ofek, E., Richardson, M., Whitelaw, R. F., 2004. Limited arbitrage and short sales restrictions: Evidence from the options markets. J. Financ. Econ. 74, 305–342.

Pástor, L., Vorsatz, M. B., 2020. Mutual fund performance and flows during the COVID-19 crisis. Rev. Asset Pric. Stud. 104, 791–833.

Pitkäjärvi, A., Suominen, M., Vaittinen, L., 2020. Cross-asset signals and time series momentum. J. Financ. Econ. 136, 63–85.

Pontiff, J., 1996. Costly arbitrage: Evidence from closed-end funds. Q. J. Econ. 111, 1135–1151.

Saarikallio, S., Erkkilä, J., 2007. The role of music in adolescents' mood regulation. Psychol. Music 35, 88–109.

Sabouni, H., 2018. The rhythm of markets. Unpublished working paper.

Shleifer, A., Vishny, R. W., 1997. The limits of arbitrage. J. Financ. 52, 35–55.

Terry, P. C., Parsons-Smith, R. L., Terry, V. R., 2020. Mood Responses Associated with COVID–19 Restrictions. Front. Psychol. 11, 3090.

Tetlock, P. C., 2007. Giving content to investor sentiment: The role of media in the stock market. J. Financ. 62, 1139–1168.

Thaler, R. H., 1987. Anomalies: Weekend, holiday, turn of the month, and intraday effects. J. Econ. Perspect. 1, 169–177.

Van den Tol, A. J., Edwards, J., 2013. Exploring a rationale for choosing to listen to sad music when feeling sad. Psychol. Music 41, 440–465.

Wang, A. Y., Young, M., 2020. Terrorist attacks and investor risk preference: Evidence from mutual fund flows. J. Financ. Econ. 137, 491–514.

Zullow, H., M., 1991. Pessimistic rumination in popular songs and news magazines predict economic recession via decreased consumer optimism and spending. J. Econ. Psychol. 12, 501–526.

Table 1

Summary Statistics. This table reports summary statistics (full sample average) on our main variables. The sample period is from January 1, 2017, to December 31, 2020. *Music Sentiment* is the weekly change in the stream-weighted average valence of the top-200 songs played on Spotify for a country (multiplied by 100). *RET* is the weekly stock market return. *VOL* is the standard deviation of daily stock market returns within the week. *SD* is the standard deviation. *AR(1)* is the first coefficient of autocorrelation.

Country	*Music Sentiment*			*RET (%)*	*VOL (%)*
	Mean	*SD*	*AR(1)*	*Mean*	*Mean*
Argentina	-0.004	0.656	-0.097	0.255	2.060
Australia	0.039	1.027	-0.190	0.304	0.951
Austria	0.054	1.347	-0.270	0.199	1.241
Belgium	0.043	1.275	-0.217	0.126	1.018
Brazil	0.057	1.021	-0.399	0.248	1.690
Canada	0.072	1.533	-0.256	0.220	0.754
Chile	-0.004	0.660	-0.043	0.071	1.208
Colombia	0.025	0.738	-0.213	0.246	1.251
Czech	0.039	1.258	-0.210	0.273	0.846
Denmark	0.042	1.201	-0.129	0.413	0.909
Finland	-0.014	1.536	-0.255	0.364	0.968
France	0.029	1.664	-0.228	0.291	0.901
Germany	0.030	1.408	-0.287	0.235	0.946
Greece	0.012	1.780	-0.257	0.061	1.530
Hong Kong	0.027	0.818	-0.084	0.185	0.899
Hungary	0.068	1.108	-0.160	0.326	1.263
Iceland	0.063	2.084	-0.295	0.249	0.961
Indonesia	-0.018	0.647	-0.040	0.220	1.214
Ireland	0.072	1.476	-0.273	0.298	1.036
Italy	-0.002	1.456	-0.229	0.285	1.079
Japan	0.013	0.681	-0.187	0.196	0.823
Latvia	0.109	1.761	-0.249	0.306	0.892
Malaysia	0.075	1.025	-0.056	0.131	0.648
Mexico	0.030	0.733	-0.202	0.177	1.251
Netherlands	0.040	1.119	-0.047	0.391	0.827
New Zealand	0.038	1.054	-0.222	0.389	0.974
Norway	0.022	1.052	-0.111	0.249	1.118
Panama	0.034	0.948	-0.190	0.066	0.711
Peru	0.025	0.537	-0.026	0.243	1.171
Philippines	0.021	0.649	-0.036	0.152	1.092
Poland	0.065	1.216	-0.283	0.233	1.260
Portugal	0.010	1.043	-0.202	0.329	0.990
Singapore	0.030	0.750	-0.043	0.192	0.799
Spain	0.015	0.863	-0.136	0.191	1.021
Sweden	0.027	1.278	-0.273	0.338	1.042
Switzerland	0.059	1.426	-0.288	0.311	0.706
Taiwan	0.000	0.876	-0.209	0.449	0.915
Turkey	-0.024	0.793	-0.178	-0.009	1.728
UK	0.059	1.630	-0.286	0.143	0.882
US	0.055	1.803	-0.288	0.341	0.802
Whole sample average	0.033	1.201	-0.191	0.242	1.059

Table 2

Validation of our Music-Based Sentiment Measure. This table reports the regression estimates of Eq. (2) from January 1, 2017, to December 31, 2020. The dependent variable, *Music Sentiment* is the weekly change in the stream-weighted average valence of the top-200 songs played on Spotify for a country. In column (1), *Positive months* is an indicator variable that equals 1 in January and March (January and September) for Northern (Southern) Hemisphere countries, and 0 otherwise. *Negative months* is an indicator variable that equals 1 in September and October (March and April) for Northern (Southern) Hemisphere countries, and 0 otherwise. In column (2), $\overline{\Delta DCC}$ is the average daily change in deseasonalized cloud cover over the week. In column (3), $\Delta COVID$ is the weekly change in the containment and closure index. In columns (1) and (4), the regressions include country and year fixed effects. In columns (2) and (3), the regressions include country and month fixed effects. Constants are not reported. White-corrected *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A4. All coefficients are multiplied by 100.

Music Sentiment	(1)		(2)		(3)		(4)	
Positive months	-0.042	(-0.98)					-0.017	(-0.40)
Negative months	-0.383***	(-9.40)					-0.376***	(-9.18)
$\overline{\Delta DCC}$			-0.183***	(-3.48)			-0.200***	(-3.66)
$\Delta COVID$					-0.043**	(-2.24)	-0.046*	(-1.94)
Fixed Effects	Country, year		Country, month		Country, month		Country, year	
R^2	1.39%		2.13%		2.09%		1.72%	
#Obs.	6,448		8,279		8,280		6,383	

Table 3

Music Sentiment and Stock Market Returns. This table reports the regression estimates from Eq. (3) from January 1, 2017, to December 31, 2020. The dependent variable is the weekly stock market return (*RET*). In Panel A, the dependent variable, *Music Sentiment*, is the weekly change in the stream-weighted average valence of the top-200 songs played on Spotify for a country. The control variables are the one-week-lagged dependent variable (RET_{t-1}), weekly return of the MSCI World index (*World RET*), contemporaneous implied volatility (*VIX*), weekly change in economic policy uncertainty (ΔEPU), weekly change in macroeconomic activity (ΔADS), and the average daily change in deseasonalized cloud cover over the week ($\overline{\Delta DCC}$). In Panel B, *Music Sentiment* is lagged by one week. All regressions include country and month fixed effects. Constants are not reported. White-corrected *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A4.

RET (%)	Panel A: Contemporaneous Music Sentiment				Panel B: One-Week-Lagged Music Sentiment			
	(1)		(2)		(3)		(4)	
Music Sentiment	12.276***	(5.03)	6.758***	(3.62)	-19.554***	(-7.52)	-5.954***	(-2.93)
World RET			0.899***	(60.84)			0.898***	(60.60)
VIX			0.008**	(2.18)			0.008**	(2.17)
ΔEPU			-0.003***	(-6.11)			-0.003***	(-6.03)
ΔADS			0.016	(0.30)			0.001	(0.02)
$\overline{\Delta DCC}$			-0.002	(-0.03)			-0.011	(-0.12)
RET_{t-1}			-0.041***	(-3.11)			-0.039***	(-2.93)
Fixed Effects	Country, month		Country, month		Country, month		Country, month	
R^2	3.62%		39.16%		3.94%		39.14%	
#Obs.	8,320		8,239		8,280		8,239	

Table 4

Robustness Checks. This table reports the results of robustness tests on the estimation of Eq. (3) from January 1, 2017, to December 31, 2020. Panel A controls for both contemporaneous and one-week-lagged music sentiment in the same regression. Panel B studies local-currency market returns. Panel C replaces *Music Sentiment* by *Music Sentiment(150)*, which excludes the daily 50 songs with the highest number of streams. Panel D includes year-month fixed effects. Panel E drops one country at a time. All regressions include country and month fixed effects unless otherwise specified. Constants are not reported. White-corrected *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A4.

Panel A: Including contemporaneous and one-week-lagged music sentiment

RET(%)	(1)		(2)	
Music Sentiment$_t$	7.669***	(3.06)	5.610***	(2.88)
Music Sentiment$_{t-1}$	-17.546***	(-6.58)	-4.463**	(-2.10)
Fixed effects	Country, month		Country, month	
Controls	No		Yes	
R^2	4.04%		39.20%	
#Obs.	8,280		8,239	

Panel B: Local-currency market returns

RET (%)	*Contemporaneous Music Sentiment*				*One-Week-Lagged Music Sentiment*			
	(1)		(2)		(3)		(4)	
Music Sentiment	7.126***	(3.46)	6.316***	(3.51)	-12.574***	(-5.75)	-6.785***	(-3.49)
Fixed Effects	Country, month		Country, month		Country, month		Country, month	
Controls	No		Yes		No		Yes	
R^2	2.87%		21.90%		3.06%		21.91%	
#Obs.	8,320		8,239		8,280		8,239	

Panel C: Music sentiment after removing the top 50 songs by number of streams

RET (%)	*Contemporaneous Music Sentiment*				*One-Week-Lagged Music Sentiment*			
	(1)		(2)		(3)		(4)	
Music Sentiment(150)	7.278***	(3.97)	3.958***	(2.67)	-10.626***	(-5.70)	-4.407***	(-2.94)
Fixed Effects	Country, month		Country, month		Country, month		Country, month	
Controls	No		Yes		No		Yes	
R^2	3.50%		39.14%		3.61%		39.15%	
#Obs.	8,314		8,234		8,274		8,233	

Panel D: Year-month fixed effects

RET (%)	*Contemporaneous Music Sentiment*				*One-Week-Lagged Music Sentiment*			
	(1)		(2)		(3)		(4)	
Music Sentiment	12.438***	(5.14)	5.790***	(3.05)	-18.316***	(-7.26)	-8.777***	(-4.33)
Fixed Effects	Country, year-month		Country, year-month		Country, year-month		Country, year-month	
Controls	No		Yes		No		Yes	
R^2	13.51%		41.75%		13.77%		41.83%	
#Obs.	8,320		8,239		8,280		8,239	

Panel E: Excluding one country

Excluded country	*Contemporaneous Music Sentiment*				*One-Week-Lagged Music Sentiment*			
	without controls		with controls		without controls		with controls	
Argentina	11.945***	(4.94)	6.615***	(3.60)	-19.474***	(-7.53)	-6.318***	(-3.13)
Australia	12.415***	(5.02)	6.852***	(3.62)	-19.940***	(-7.57)	-6.312***	(-3.06)
Austria	10.977***	(4.48)	5.798***	(3.08)	-19.408***	(-7.43)	-5.756***	(-2.81)
Belgium	12.277***	(4.96)	6.720***	(3.56)	-19.342***	(-7.33)	-5.780***	(-2.80)
Brazil	11.659***	(4.80)	6.113***	(3.32)	-18.710***	(-7.23)	-5.237***	(-2.60)
Canada	12.621***	(5.02)	7.209***	(3.73)	-19.329***	(-7.20)	-6.208***	(-2.94)
Chile	11.820***	(4.84)	6.552***	(3.51)	-19.050***	(-7.31)	-5.543***	(-2.72)
Colombia	12.182***	(5.00)	6.647***	(3.56)	-18.676***	(-7.19)	-5.229**	(-2.57)
Czech	12.188***	(4.90)	6.490***	(3.42)	-19.577***	(-7.38)	-5.567***	(-2.69)
Denmark	12.403***	(5.02)	7.016***	(3.71)	-19.729***	(-7.46)	-6.250***	(-3.02)
Finland	12.124***	(4.89)	6.875***	(3.60)	-20.106***	(-7.56)	-6.488***	(-3.10)
France	13.237***	(5.30)	7.475***	(3.87)	-20.516***	(-7.65)	-6.183***	(-2.91)
Germany	11.658***	(4.71)	6.538***	(3.42)	-19.804***	(-7.50)	-6.039***	(-2.90)
Greece	13.208***	(5.43)	7.587***	(4.11)	-20.131***	(-7.95)	-6.741***	(-3.48)
Hong Kong	12.145***	(4.94)	6.697***	(3.56)	-19.589***	(-7.47)	-5.892***	(-2.88)
Hungary	12.026***	(4.90)	6.448***	(3.45)	-19.384***	(-7.40)	-5.883***	(-2.88)
Iceland	12.726***	(4.96)	6.279***	(3.25)	-20.616***	(-7.59)	-6.310***	(-3.04)
Indonesia	12.593***	(5.14)	6.913***	(3.70)	-19.555***	(-7.49)	-6.145***	(-3.01)
Ireland	12.263***	(4.92)	6.785***	(3.55)	-19.500***	(-7.34)	-6.077***	(-2.91)
Italy	11.743***	(4.73)	6.458***	(3.38)	-19.380***	(-7.32)	-5.733***	(-2.76)
Japan	12.446***	(5.07)	6.742***	(3.58)	-19.892***	(-7.59)	-6.014***	(-2.93)
Latvia	13.103***	(5.16)	7.147***	(3.71)	-20.729***	(-7.65)	-6.771***	(-3.22)
Malaysia	12.493***	(5.06)	6.849***	(3.63)	-19.790***	(-7.51)	-6.021***	(-2.92)
Mexico	11.990***	(4.91)	6.647***	(3.56)	-18.950***	(-7.27)	-5.646***	(-2.77)
Netherlands	12.404***	(5.01)	6.675***	(3.51)	-19.567***	(-7.41)	-6.040***	(-2.91)
New Zealand	12.363***	(5.02)	6.722***	(3.57)	-19.219***	(-7.31)	-5.674***	(-2.76)
Norway	12.230***	(5.00)	6.787***	(3.61)	-19.018***	(-7.26)	-5.463***	(-2.66)
Panama	12.403***	(5.03)	7.005***	(3.71)	-19.336***	(-7.35)	-5.796***	(-2.82)
Peru	12.427***	(5.08)	7.046***	(3.77)	-19.316***	(-7.41)	-5.744***	(-2.82)
Philippines	12.255***	(5.00)	6.622***	(3.54)	-19.201***	(-7.35)	-5.475***	(-2.69)
Poland	12.628***	(5.11)	6.804***	(3.61)	-20.261***	(-7.70)	-6.355***	(-3.08)
Portugal	12.027***	(4.83)	6.932***	(3.66)	-18.638***	(-7.14)	-6.066***	(-2.95)
Singapore	12.173***	(4.96)	6.682***	(3.55)	-19.498***	(-7.45)	-5.965***	(-2.91)
Spain	12.235***	(5.00)	6.615***	(3.52)	-18.952***	(-7.26)	-5.428***	(-2.65)
Sweden	12.253***	(4.94)	6.792***	(3.57)	-20.068***	(-7.58)	-6.415***	(-3.09)
Switzerland	12.727***	(5.07)	7.326***	(3.82)	-19.964***	(-7.45)	-6.065***	(-2.89)
Taiwan	12.246***	(4.98)	6.938***	(3.69)	-19.692***	(-7.50)	-6.176***	(-3.01)
Turkey	11.289***	(4.65)	6.022***	(3.26)	-18.411***	(-7.09)	-5.121**	(-2.54)
UK	12.269***	(4.87)	6.624***	(3.42)	-19.608***	(-7.29)	-5.974***	(-2.82)
US	12.859***	(5.06)	7.320***	(3.71)	-19.669***	(-7.24)	-6.399***	(-2.97)

Table 5

Music Sentiment and Stock Market Returns at Daily Frequency. This table reports the daily regression estimates from Eq. (3) from January 1, 2017, to December 31, 2020. The dependent variable is the daily stock market return (*RET*). The main independent variable is *Music Sentiment*, the daily change in the stream-weighted average valence of the top-200 songs played on Spotify for a country, contemporaneous or lagged by one to five days. *Music Sentiment$_{d:d-1}$* is the average of the same day and one-day-lagged music sentiment. The control variables are the one-to-five-day lagged values of the dependent variable and the change in deseasonalized cloud cover ($\overline{\Delta DCC}$), as well as contemporaneous, next-day, and prior-day daily returns of the MSCI World index (*World RET*), daily change in economic policy uncertainty (*ΔEPU*), daily change in macroeconomic activity (*ΔADS*), and implied volatility (*VIX*). All regressions include country, month, and day-of-the-week fixed effects. Constants are not reported. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A4.

RET$_d$ (%)	(1)		(2)		(3)		(4)		(5)		(6)	
Music Sentiment$_{d:d-1}$	2.713**	(2.01)									3.092**	(2.20)
Music Sentiment$_{d-2}$			0.089	(0.10)							0.339	(0.37)
Music Sentiment$_{d-3}$					-0.273	(-0.31)					-0.178	(-0.20)
Music Sentiment$_{d-4}$							0.483	(0.57)			0.177	(0.20)
Music Sentiment$_{d-5}$									-2.430***	(-2.79)	-2.534***	(-2.85)
RET controls	d-1, …, d-5		d-1, …, d-5		d-1, …, d-5		d-1, …, d-5		d-1, …, d-5		d-1, …, d-5	
$\overline{\Delta DCC}$ *controls*	d-1, …, d-5		d-1, …, d-5		d-1, …, d-5		d-1, …, d-5		d-1, …, d-5		d-1, …, d-5	
World RET controls	d-1, d, d+1		d-1, d, d+1		d-1, d, d+1		d-1, d, d+1		d-1, d, d+1		d-1, d, d+1	
VIX controls	d-1, d, d+1		d-1, d, d+1		d-1, d, d+1		d-1, d, d+1		d-1, d, d+1		d-1, d, d+1	
ΔEPU controls	d-1, d, d+1		d-1, d, d+1		d-1, d, d+1		d-1, d, d+1		d-1, d, d+1		d-1, d, d+1	
ΔADS controls	d-1, d, d+1		d-1, d, d+1		d-1, d, d+1		d-1, d, d+1		d-1, d, d+1		d-1, d, d+1	
Fixed Effects	Country, month, day		Country, month, day		Country, month, day		Country, month, day		Country, month, day		Country, month, day	
R^2	25.72%		25.71%		25.71%		25.71%		25.72%		25.73%	
#Obs.	39,391		39,391		39,391		39,391		39,391		39,391	

Table 6

Effect of Music Sentiment on Stock Market Returns and Trading Restrictions. This table reports the regression estimates from Eq. (4) from January 1, 2017, to December 31, 2020. The dependent variable is the weekly stock market return (*RET*). In Panel A, the main independent variable is *Music Sentiment*, the weekly change in the stream-weighted average valence of the top-200 songs played on Spotify for a country. The control variables are the one-week-lagged dependent variable (RET_{t-1}), weekly return of the MSCI World index (*World RET*), contemporaneous implied volatility (*VIX*), weekly change in economic policy uncertainty (ΔEPU), weekly change in macroeconomic activity (ΔADS), and the average daily change in deseasonalized cloud cover over the week ($\overline{\Delta DCC}$). *BAN* is a dummy variable equal to 1 if country *i's* stock market is under a trading restriction for the full week *t*, and 0 otherwise. In Panel B, *Music Sentiment* and *BAN* are lagged by one week. All regressions include country and month fixed effects. Constants are not reported. White-corrected *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A4. Table A6 provides the start and end periods of short-sale bans during the COVID-19 pandemic by country.

RET (%)	Panel A: Contemporaneous Music Sentiment				Panel B: One-Week-Lagged Music Sentiment			
	(1)		(2)		(3)		(4)	
Music Sentiment	9.923***	(4.08)	6.197***	(3.32)	-17.026***	(-6.60)	-4.379**	(-2.18)
Music Sentiment × BAN	105.967***	(4.99)	27.988*	(1.66)	-113.763***	(-5.37)	-74.295***	(-3.55)
BAN	0.329	(1.09)	-0.292	(-1.13)	0.337	(1.17)	-0.303	(-1.16)
World RET			0.897***	(60.59)			0.898***	(60.64)
VIX			0.010**	(2.52)			0.010***	(2.72)
ΔEPU			-0.003***	(-6.11)			-0.003***	(-6.00)
ΔADS			0.029	(0.53)			0.002	(0.05)
$\overline{\Delta DCC}$			-0.003	(-0.03)			-0.010	(-0.11)
RET_{t-1}			-0.041***	(-3.10)			-0.035***	(-2.65)
Fixed Effects	Country, month		Country, month		Country, month		Country, month	
R^2	4.12%		39.21%		4.46%		39.39%	
#Obs.	8,320		8,239		8,280		8,239	

Table 7

Effect of Music Sentiment on Small vs. Large Stock Market Returns. This table reports the regression estimates from Eq. (3) from January 1, 2017, to December 31, 2020. The dependent variable is either the weekly domestic MSCI small-cap or large-cap index return. In Panel A, the main independent variable is *Music Sentiment*, the weekly change in the stream-weighted average valence of the top-200 songs played on Spotify for a country. The control variables are the one-week-lagged stock market return (RET_{t-1}), weekly return of the MSCI World index (*World RET*), contemporaneous implied volatility (*VIX*), weekly change in economic policy uncertainty (ΔEPU), weekly change in macroeconomic activity (ΔADS), and the average daily change in deseasonalized cloud cover over the week ($\overline{\Delta DCC}$). In Panel B, *Music Sentiment* is lagged by one week. All regressions include country and month fixed effects. Constants are not reported. White-corrected *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A4.

RET (%)	Panel A: Contemporaneous Music Sentiment				Panel B: One-Week-Lagged Music Sentiment			
	(1)		(2)		(3)		(4)	
	MSCI Small Index		*MSCI Large Index*		*MSCI Small Index*		*MSCI Large Index*	
Music Sentiment	10.721***	(4.48)	7.427***	(2.93)	-8.409***	(-3.49)	-6.996***	(-2.79)
Controls	Yes		Yes		Yes		Yes	
Fixed Effects	Country, month		Country, month		Country, month		Country, month	
R^2	43.2%		38.7%		43.2%		38.7%	
#Obs.	7,415		7,415		7,415		7,415	
p-value of one-sided Wald test of coefficient equality	0.078				0.263			

Table 8

Music Sentiment and Stock Market Volatility. This table reports the regression estimates from Eq. (5) from January 1, 2017, to December 31, 2020. The dependent variable is weekly stock market volatility (*VOL*) calculated as the standard deviation of the daily stock market return within the week. The main independent variable is the absolute of *Music Sentiment*, the absolute weekly change in the stream-weighted average valence of the top-200 songs played on Spotify for a country. The control variables are the one-week-lagged dependent variable (VOL_{t-1}), one-week-lagged stock market return (RET_{t-1}), weekly change in macroeconomic activity (ΔADS), weekly change in economic policy uncertainty (ΔEPU), average daily change in deseasonalized cloud cover over the week ($\overline{\Delta DCC}$), and weekly return of the MSCI World index (*World RET*). All regressions include country and month fixed effects. Constants are not reported. White-corrected *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A4.

VOL (%)	(1)		(2)	
|*Music Sentiment*|	4.251***	(4.34)	2.394***	(2.94)
World RET			-0.046***	(-11.54)
ΔEPU			0.000	(1.10)
ΔADS			-0.010	(-0.67)
$\overline{\Delta DCC}$			-0.012	(-0.59)
VOL_{t-1}			0.444***	(29.89)
RET_{t-1}			-0.019***	(-5.84)
Fixed Effects	Country, month		Country, month	
R^2	20.48%		38.38%	
#Obs.	8,320		8,239	

Table 9

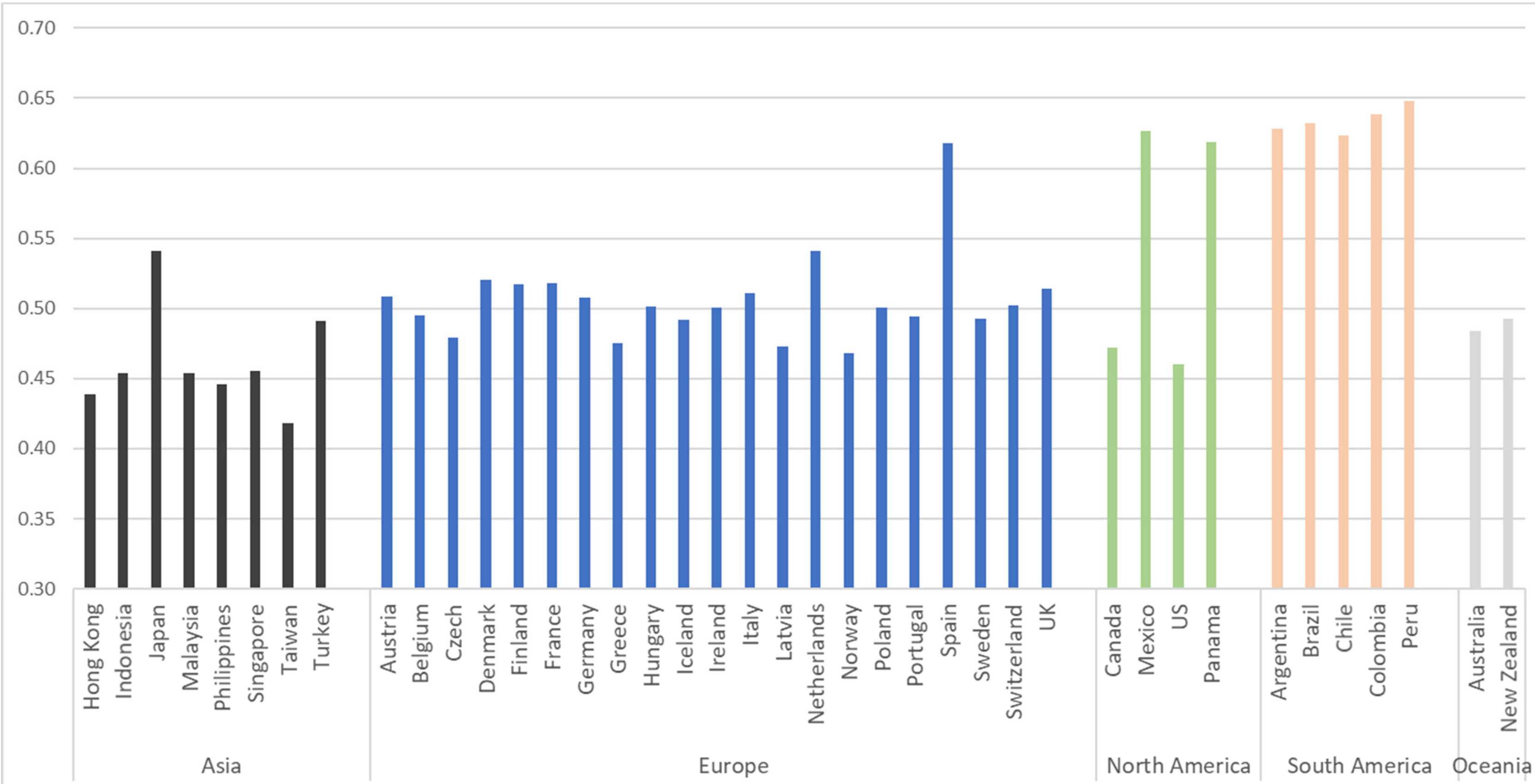
Music Sentiment and Net Equity Mutual Fund Flows. This table reports the regression estimates from Eq. (6) from January 1, 2017, to December 31, 2020. The dependent variable is *Net Flows,* the weekly net fund flow scaled by the fund's assets under management at the end of the previous week. The main independent variables are the contemporaneous and one-week-lagged *Music Sentiment*, the weekly change in the stream-weighted average valence of the top-200 songs played on Spotify for a country. The control variables are the one-week-lagged dependent variable (*Net Flows$_{t-1}$)*, one-week-lagged stock market return (*RET$_{t-1}$*), contemporaneous implied volatility (*VIX*), weekly change in economic policy uncertainty (*ΔEPU*), weekly change in macroeconomic activity (*ΔADS*), average daily change in deseasonalized cloud cover over the week ($\overline{\Delta DCC}$), and weekly return of the MSCI World index (*World RET*). All regressions include fund and month fixed effects. Constants are not reported. White-corrected *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A4.

Net Flows (%)	(1)		(2)		(3)	
Music Sentiment$_t$	0.147*	(1.81)			0.212***	(2.53)
Music Sentiment$_{t-1}$			0.166**	(2.02)	0.229***	(2.68)
World RET	0.655***	(9.70)	0.673***	(9.96)	0.668***	(9.87)
VIX	-0.005***	(-29.62)	-0.005***	(-29.62)	-0.005***	(-29.62)
ΔEPU	0.000	(-1.48)	0.000	(-1.36)	0.000	(-1.52)
ΔADS	0.019***	(9.47)	0.019***	(9.44)	0.019***	(9.63)
$\overline{\Delta DCC}$	-0.004	(-0.72)	-0.005	(-0.94)	-0.004	(-0.80)
RET$_{t-1}$	0.034	(0.61)	0.034	(0.61)	0.025	(0.44)
Net Flows$_{t-1}$	0.176***	(23.53)	0.176***	(23.53)	0.176***	(23.53)
Fixed Effects	Fund, month		Fund, month		Fund, month	
R^2	10.90%		10.90%		10.90%	
#Obs.	1,550,261		1,550,261		1,550,261	

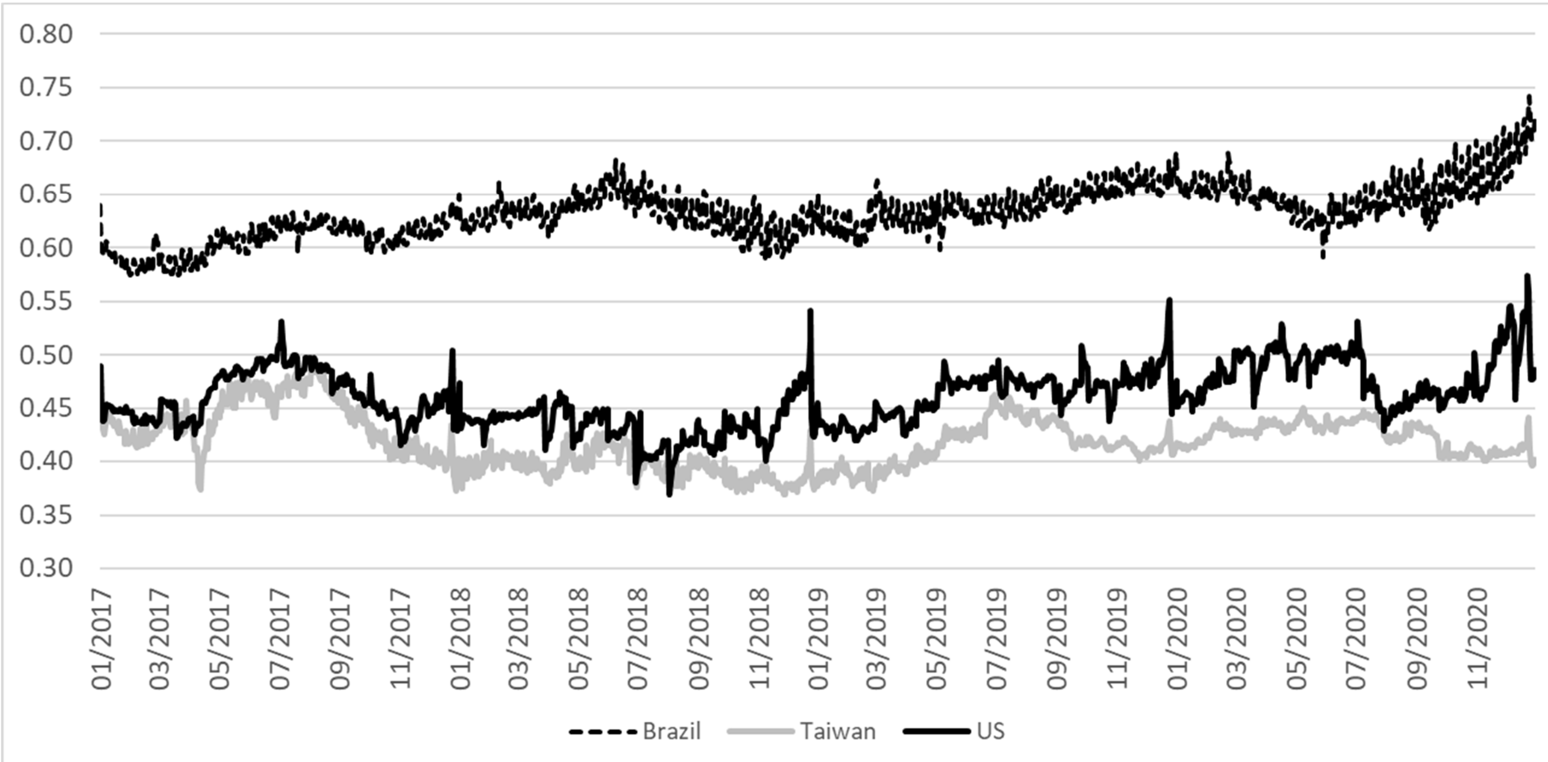
Table 10

Music Sentiment and Government Bond Returns. This table reports the regression estimates from Eq. (3) from January 1, 2017, to December 31, 2020, replacing stock market index returns by government bond index returns. The dependent variable is the weekly government bond index return (*Gov Bond RET*). In Panel A, the main independent variable is *Music Sentiment*, the weekly change in the stream-weighted average valence of the top-200 songs played on Spotify for a country. The control variables are the one-week-lagged dependent variable (*Gov Bond RET*$_{t-1}$), weekly return of the MSCI World index (*World RET*), contemporaneous implied volatility (*VIX*), weekly change in economic policy uncertainty (*ΔEPU*), weekly change in macroeconomic activity (*ΔADS*), and the average daily change in deseasonalized cloud cover over the week ($\overline{\Delta DCC}$). All regressions include country and month fixed effects. Constants are not reported. White-corrected *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Variable definitions are in Table A4.

Gov Bond RET (%)	Panel A: Contemporaneous Music Sentiment				Panel B: One-Week-Lagged Music Sentiment			
	(1)		(2)		(3)		(4)	
Music Sentiment	-1.081***	(-3.13)	-0.723**	(-2.08)	-0.037	(-0.11)	-0.314	(-0.89)
World RET			-0.016***	(-5.89)			-0.017***	(-6.09)
VIX			0.003***	(4.04)			0.003***	(4.08)
ΔEPU			0.000***	(-3.62)			0.000***	(-3.78)
ΔADS			0.014	(1.46)			0.015	(1.56)
$\overline{\Delta DCC}$			-0.025*	(-1.70)			-0.024	(-1.62)
Gov Bond RET$_{t-1}$			0.006	(0.23)			0.003	(0.14)
Fixed Effects	Country, month		Country, month		Country, month		Country, month	
R^2	3.01%		4.72%		2.82%		4.66%	
#Obs.	5,200		5,146		5,175		5,146	



1. Stream-weighted average valence of top-200 songs by geographical regions and country. This figure plots the average daily stream-weighted average valence (*SWAV*) per country over our sample period from January 1, 2017, to December 31, 2020. The 40 countries in our sample are grouped by geographical regions.



2. Daily stream-weighted average valence of top-200 songs. This figure plots time series of daily stream-weighted average valence (*SWAV*) over our sample period from January 1, 2017, to December 31, 2020, for the U.S., Brazil, and Taiwan.