Music Sentiment and Stock Returns Around the World*

Alex Edmans [a]
London Business School, CEPR, and ECGI

Adrian Fernandez-Perez [b]
Auckland University of Technology

Alexandre Garel [c]
Audencia Business School

Ivan Indriawan [d]
Auckland University of Technology

Current draft: January 30, 2020

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 require us to pre-specify certain mood-affecting events, nor assume the extent of their impact on investors. We validate our music-based sentiment measure by documenting a correlation with mood swings induced by seasonal factors and weather conditions. We find that music sentiment is positively correlated with same-week 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 for countries with greater limits to arbitrage. Music sentiment also predicts increases in net mutual fund flows and absolute sentiment precedes a rise in stock market volatility.

JEL Classification: G12; G14

Keywords: Investor Sentiment; Investor Mood; Behavioral Finance

* We thank David Hirshleifer for helpful comments.
[a] aedmans@london.edu, London Business School, Regent's Park, London NW1 4SA.
[b] adrian.fernandez@aut.ac.nz, Auckland University of Technology, Private Bag 92006, 1142, Auckland, New Zealand.
[c] agarel@audencia.com, Audencia Business School, 8 Route de la Jonelière, 44312 Nantes, France.
[d] ivan.indriawan@aut.ac.nz, Auckland University of Technology, Private Bag 92006, 1142, Auckland, New Zealand.

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 that it affects the sentiment of the marginal investor.

In this paper, we take a different approach. Rather than studying shocks to sentiment, we wish to measure a country's *actual* sentiment at a point in time. Actual sentiment may be driven by a wide variety of different events and thus does not require us to pre-specify a particular set of events. In addition, actual sentiment aims to capture the *extent* to which events affect investor mood. It may be that a country has lost an international soccer match, but the effect on mood is muted either because the loss was predictable or soccer is not a popular sport in that particular country. Thus, rather than using an exogenous shock that is assumed to affect how people are feeling, we seek an endogenous measure that reflects it. We wish this measure to be available at 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, there is no 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 is based on research from the psychology literature that individuals reflect their mood in their music choices. In particular, a range of studies document "emotion congruity" – that music is used to validate emotion. Cantor and Zillman (1973) induce emotions in subjects by showing them films and find that they then prefer emotionally congruent music. North and Hargreaves (1996) show that participants' preference for music matches their current emotional states. Saarikallio and Erkkilä (2007) document that subjects who are sad or angry are inclined to listen to sad music to express their emotions or attain closure. 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. Hunter, Schellenberg, and Griffith (2011) find that the typical preference for upbeat music is eliminated after inducing a sad mood. Van den Tol and Edwards (2013) find that people listen to sad music after experiencing negative circumstances due to feeling connected with the music.

Listening data is available on a large scale from Spotify, the leading online music platform worldwide. It had 286 million monthly active users as of the first quarter of 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 the Spotify users were above 24 years old, while more than 30% of users are older than 45.[1] 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 choose to listen to songs whose sentiment contrasts their actual mood to attenuate mood swings caused by exogenous events – for example, attenuating negative sentiment by playing an upbeat song. Such a concern is inconsistent with the above papers, which find that people listen to music that reflects their emotions rather than attempting to neutralize it. 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 validation test using

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

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-based 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 8.5 basis points (bps), or 4.5% annualized. This effect reverses over the next week: a one standard deviation increase in music sentiment predicts a lower next-week return of 6 bps, or -2.8% 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). We obtain similar results with a daily analysis – music sentiment is associated with significantly higher next-day stock returns, but lower returns on the following days. Our results hold for both dollar and local currency returns, and when excluding one country at a time to attenuate concerns that they may be driven by a specific country.

To further test whether national sentiment is driving our results, we perform a series of additional analyses. First, the impact of sentiment should be stronger when there are higher limits to arbitrage (Baker and Wurgler, 2006, 2007). Over our sample period, some countries implemented bans on short-selling at the beginning of the COVID-19 pandemic, limiting arbitrage opportunities. We conduct difference-in-difference 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 an out-of-sample test, we move from studying equity indices to equity mutual funds. Prior literature shows that mutual fund flows are affected by investor sentiment (e.g., Ben-Raphael, Kandel, and Wohl, 2011, 2012). We indeed find that music sentiment is a significantly positive predictor of next-week net fund flows.

Our study contributes to the literature on the effect of investor sentiment on the stock market. Prior studies have introduced a range of investor sentiment measures, each with their unique strengths, but also with 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., 2019), and clock changes (Kamstra, Kramer, and Levi, 2000). While powerful where available, such sentiment measures do not exist for most of the year. In addition, since they are discrete, they show that sudden shocks to sentiment affect asset prices but do not have implications for more moderate changes. The market-based sentiment index of Baker and Wurgler (2006) and surveys (used by, e.g., Brown and Cliff, 2005; Lemmon and Portniaguina, 2006) are continuous measures, but available at a lower frequency and may capture economic forces other than sentiment. Other studies have used weather variables such as cloud cover (Hirshleifer and Shumway, 2003; Goetzmann et al., 2015) or daylight hours (Kamstra, Kramer, and Levi, 2003). These measures are both continuous and available at 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. Our contribution is to develop a continuous, high-frequency, country-level measure that captures direct manifestations of citizens' mood.

More closely related is Gao, Rhen, and Zhang (2020), who use textual analysis of internet searches to measure sentiment, as developed in Da, Engelberg, and Gao (2015).[2] Like us, they 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 the global comparability of the sentiment measure. Loughran and McDonald (2016) review other limitations of textual analysis, such as disambiguating sentences, which likely also vary across languages. While our music-based sentiment measure also involves subjectivity in experts' opinions of song valence, similar to the subjectivity in choosing a set of words for a particular language, the sentiment measure applies to songs all over the world, which increases comparability. While the same word may have multiple meanings in different languages, 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 there are universal properties of music 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 capture.

This paper substantially expands and updates a preliminary paper by Fernandez-Perez, Garel, and Indriawan (2020) which documents a correlation between weekly music sentiment and stock returns in the U.S. Since the music sentiment measure is only available for a short

[2] Other papers using textual analysis to construct a sentiment measure include Tetlock (2007), Das and Chen (2007), Bollen, Mao, and Zeng (2011), and Garcia (2014). Our paper is also related to studies investigating high-frequency proxies of sentiment using non-textual sources. For instance, Obaid and Pukthuanthong (2019) measure sentiment through a sample of editorial news photos.

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 conduct cross-country analyses exploiting variation in limits to arbitrage. We also study the impact of sentiment on volatility and mutual fund flows.

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 additional analyses. Section 4 concludes.

1. Data and Variable Measurement

1.1 Music sentiment

To measure music sentiment, we collect data from Spotify. Starting from January 1, 2017, Spotify releases, per country, daily statistics of the top 200 songs by the total number of streams. As of August 2020, Spotify provides data for 62 countries. We only select countries where Spotify data is available since January 1, 2017, and MSCI stock market indices are available from Refinitiv (formerly Thomson Reuters). This results in a total sample of 40 countries over the sample period from January 1, 2017 to August 28, 2020.[3] We identify over 54,000 unique songs with over 450 billion streams in total. On average, there are 8.4 million streams daily, with around 42,000 streams per song.

In addition to the top-200 songs, Spotify also has an algorithm that classifies a song's *valence*, which measures the musical positivity conveyed by a song and ranges from 0 to 1. This algorithm is trained on positivity ratings by musical experts and can be linked to any song using the Spotify application-programming interface. Songs with high valence sound more positive (e.g., happy, cheerful, euphoric), while songs with low valence sound more negative

[3] We drop Bulgaria, Estonia, India, Israel, Lithuania, Luxembourg, Romania, South Africa, Thailand, and Vietnam since their Spotify data is only available for less than one year. We also drop Bolivia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Malta, Nicaragua, Paraguay, Slovakia and Uruguay due to unavailability of MSCI stock market data.

(e.g., sad, depressed, angry). Table A1 reports the songs with the highest and lowest non-zero valance per country in our sample period. We then construct a stream-weighted average valence (henceforth *SWAV*) across the top-200 songs for each day *d* and country *i* as follows:

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

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.*

Figure 1 shows a chart of the full sample average *SWAV* across countries. We observe that South American countries have a higher average *SWAV*, while Asian countries have a lower average *SWAV*.

Insert Figure 1 here

To match our music sentiment with the stock market and macroeconomic data, we aggregate the information at a weekly level to avoid non-synchronicity between the opening and closing times of the stock markets and the time of the day that Spotify reports their daily statistics. Such an issue may lead to instances where the daily measure of *SWAV* would partially lead the daily measure of stock market return and other instances where it would lag it. 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, labeled *Music Sentiment*, is thus given by:

$$Music\ Sentiment_{i,t} = SWAV_{i,t} - SWAV_{i,t-1} \qquad (1b)$$

where $SWAV_{i,t}$ is the stream-weighted average valence for week *t* (taken every Friday). *Music Sentiment* is, therefore, 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 A2 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 -0.019% (Argentina) to 0.077% (Latvia). Weekly stock market returns range from -0.05% (Turkey) to 0.39% (Taiwan) and weekly stock market volatility ranges from 0.61% (Malaysia) to 2.07% (Argentina).

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 over the sample period. We first draw on prior literature to identify seasonal factors likely to affect individuals' moods (e.g., Thaler, 1987; Kamstra, Kramer, and Levi, 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). In 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 observed both in the Northern and in Southern Hemispheres, except that for the latter, it is 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 zero (clear sky) to eight (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.[4] Since 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 deseasonalized cloud cover within a week in our validation test ($\overline{\Delta DCC}$).[5] 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.

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

[4] 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). Both results are qualitatively similar.

[5] Hirshleifer and Shumway (2003) show that both the change and level of cloudiness are related to mispricing.

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

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

where $Positive\ Months$ is an indicator variable that equals one for January and March for Northern Hemisphere countries (January and September for Southern Hemisphere countries – we do not shift January since it remains the New Year in the Southern Hemisphere) and 0 otherwise, $Negative\ Months$ is an indicator variable that equals one in September and October for Northern Hemisphere countries (March and April for Southern Hemisphere countries) and 0 otherwise[6], and $\overline{\Delta DCC}_{i,t}$ is the average daily change in deseasonalized cloud cover within week *t*. We estimate equations (2) using Ordinary Least Squares (OLS) and report White-corrected t-statistics, which are robust to heteroscedasticity. Table A3 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 increasing mood periods (*Positive Months*) are positively but insignificantly associated with an increase in our music-based sentiment measure while decreasing mood periods (*Negative Months*) are significantly negatively associated with music-based sentiment, with a t-statistic exceeding 7. 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) includes all of the above explanatory variables, and shows that negative months and increases in cloudiness continue to be associated with a decline in music sentiment. These results suggest that our music-based sentiment measure captures mood swings of a country's individuals

[6] 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.

caused by well-established mood-affecting factors.[7] 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

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 ($\overline{\Delta DCC}$) since 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 on the domestic market. Thus, we include the contemporaneous weekly world return (*World RET)* and three macroeconomic variables. Since 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 US 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

[7] Table A4 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). In addition, the daily increase in cloud cover remains negatively associated with music sentiment.

uncertainty (*ΔEPU*) developed by Baker, Bloom, and Davis (2016) and taken from Scott Baker's website.[8] We also control for the weekly change in weekly U.S. macroeconomic activity using the Aruoba, Diebold, and Scotti (2009) index (*ΔADS*) from the Federal Reserve website.[9] Finally, we control for the 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 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 time-varying global drivers, including season-induced mood swings not captured by our music-based sentiment measure.

Table 3, Panel A reports the estimation results of equation (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 8.5 bps (4.5% annualized), significant at the 1% level. Panel B reports the estimation results of equation (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 6 bps (-2.8% annualized), significant at the 5% 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.

---

[8] 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.

[9] 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.

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

Insert Table 3 here

Table 4 reports the results of robustness tests. Panel A demonstrates that the results are robust to estimating equation (3) with local currency returns, to address the concern that sentiment affects the exchange rate. Panel B reports the results of Table 3 when excluding one country at a time from our sample. It shows that our main results are not driven by a specific country.

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, it might be that negative stock returns induce 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 positive (negative) mood later in the week.

Table 5 thus studies the link between daily music sentiment and next-day stock returns. In the daily setting, we include up to five lags of music sentiment, 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 since Table A4 shows that they are significantly correlated with music sentiment. We find that daily music sentiment is positively correlated with the next-day index return and negatively correlated with the return five days later. Both coefficients are significant at the 5% level or better. In economic terms, a one standard deviation increase in daily music sentiment is associated with a higher next-day return of 1.1 bps (2.8% annualized) and a subsequent lower daily return of 1.4 bps five days later (-3.5% 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 changes in stock prices.

Insert Table 5 here

3. Additional Analyses

3.1.1 Limits to arbitrage

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-difference analyses around plausibly exogenous shocks to limits to arbitrage. Specifically, we exploit the introduction of short-selling bans by some of our sample countries during the COVID-19 pandemic as a shock that increased limits to arbitrage. Prior studies support the introduction of short-selling restrictions as hindering arbitrage. 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 that the effect of sentiment is stronger in countries with short-selling bans during the global financial crisis.

Table A5 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." These bans were unexpected and country-specific; many countries exposed to COVID-19 did not introduce them. We estimate the following difference-in-difference regression:

$$RET_{i,t} = \alpha + \beta_1 Music\ Sentiment_{i,t} + \beta_2 Music\ Sentiment_{i,t} \times BAN_{i,t}$$

$$+ \beta_3 BAN_{i,t} + \sum \Gamma \cdot Controls_{i,t} + \varepsilon_{i,t} \quad (4)$$

where *BAN* equals 1 if a country *i*'s stock market is subject to a short-selling ban for the full week *t*, and 0 otherwise. We expect the stock price to be more responsive to changes in music sentiment when limits to arbitrage are greater, i.e., β_2 to be positive (negative) for current (lagged) music sentiment.

Panels A and B of Table 6 report the estimation results of equation (4) for current and one-week lagged music sentiment, respectively. We find that the coefficient of the interaction term is positive for current returns and negative for future returns. Music sentiment is associated with greater contemporaneous stock returns and subsequent reversals under short-selling bans. Specifically, a one standard deviation increase in music sentiment is associated with a 39 bps greater increase in the contemporaneous return in ban weeks versus non-ban weeks, and a 98 bps greater decrease in future returns[10]. 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

---

[10] While 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 short-selling bans only, focus on EU countries as they are likely to have been exposed to COVID-19 to a similar degree, compare the association in post-ban months to the one in the same number of pre-ban months, and interact the ban dummy with the other control variables.

3.1.2 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) since 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. We expect weekly stock market volatility to be positively affected by contemporaneous weekly absolute music sentiment. We study absolute music sentiment because large changes in sentiment in either direction should lead to 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:

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

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

Table 7 reports the estimation results of equation (5). We document a strong contemporaneous correlation between absolute music sentiment and stock market volatility. A one standard deviation increase in absolute music sentiment corresponds with a contemporaneous 3 bps increase in stock market volatility, which is 3 % of the average weekly volatility of 1.042%. Our findings on stock market returns and stock market volatility paint a consistent picture of sentiment-induced stock price deviations from fundamentals.

Insert Table 7 here

3.1.3 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, positive mood should lead investors to be optimistic and thus buy into funds; indeed Ben-Raphael, 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 one-week lagged music sentiment because it takes several days for flows to be settled and reported (Da, Engelberg, and Gao, 2015). 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 US dollars. We remove duplicates (funds with exactly the same time series of net flows and size) and funds with less than one observation per week on average (i.e., less 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 Pastor 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 8,340 equity funds from 31 different countries and around 1,432,000 fund-week observations[11]. 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 in the previous week. We then estimate the following panel regression:

$$Net\ Flows_{f,i,t} = \alpha + \beta_1 Music\ Sentiment_{i,t-1} + \sum \Gamma \cdot Controls_{i,t} + \varepsilon_{i,t} \tag{6}$$

[11] 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.

where $Net\ Flows_{f,i,t}$ is the weekly size-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 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 8 reports the results of the estimation of equation (6). We find that music sentiment is positively related to future equity fund flows. A one standard deviation increase in music sentiment corresponds to an average increase in net fund flows of 0.0031%. Since the average fund size is $963 million, a one standard deviation increase in music sentiment corresponds to a weekly (annual) net flow of about $30,000 ($1.5 million).[12] The former is comparable with the average weekly net flow in our sample of -$30,672. Our results suggest significant inflows to the equity market the week following an increase in music sentiment. This finding is consistent with the argument that music sentiment affects investment decisions.

Insert Table 8 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 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, are associated with a significant decrease in our music-based sentiment measure.

In our main findings, we document a positive and significant relation between music sentiment and contemporaneous market returns, controlling for world market returns,

[12] 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 is a similar order of magnitude to our effect, although larger since terrorism likely has a larger effect than sentiment reflected in music.

seasonalities, and macroeconomic variables. We also find a significant price reversal the following week. Hence, 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 for countries with greater limits to arbitrage, such as those that implement short-selling restrictions during the COVID-19 pandemic. Music sentiment also predicts increases in net mutual fund flows and absolute sentiment precedes a rise in stock market volatility. Overall, our study provides evidence that the actual sentiment of a country's citizens significantly affects asset prices.

References

Aruoba, S. B., Diebold, F. X., and Scotti, C. (2009). Real-time measurement of business conditions. *Journal of Business and Economic Statistics* 27, 417-427.

Baker, M., and Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *Journal of Finance* 61, 1645-1680.

Baker, M., and Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives* 21, 129-152.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics* 131, 1593-1636.

Barber, B. M., Odean, T., and Zhu, N. (2009). Systematic noise. *Journal of Financial Markets* 12, 547-569.

Ben-Rephael, A., Kandel, S., and Wohl, A. (2011). The price pressure of aggregate mutual fund flows. *Journal of Financial and Quantitative Analysis*, 46, 585-603.

Ben-Rephael, A., Kandel, S., and Wohl, A. (2012). Measuring investor sentiment with mutual fund flows. *Journal of Financial Economics*, 104, 363-382.

Birru, J. (2018). Day of the week and the cross-section of returns. *Journal of Financial Economics* 130, 182-214.

Black, F. (1986). Noise. *Journal of Finance* 41, 529-543.

Bollen, J., Mao, H., and Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science* 2, 1-8.

Bris, A., Goetzmann, W. N., and Zhu, N. (2007). Efficiency and the bear: Short sales and markets around the world. *Journal of Finance* 62, 1029-1079.

Brown, G. W., and Cliff, M. T. (2005). Investor sentiment and asset valuation. *Journal of Business* 78, 405-440.

Brown, S. J., Goetzmann, W. N., Hiraki, T., Shirishi, N., and Watanabe, M. (2003). Investor sentiment in Japanese and US daily mutual fund flows. Working Paper.

Brusa, F., Savor, P., and Wilson, M. (2020). One central bank to rule them all. *Review of Finance* 24, 263-304.

Cantor, J. R., and Zillman, D. (1973). Resentment toward victimized protagonists and severity of misfortunes they suffer as factors in humor appreciation. *Journal of Experimental Research in Personality* 6, 321-329.

Chen, Y., Goyal, A., Veeraraghavan, M., and Zolotoy, L. (2019). Terrorist attacks, investor sentiment, and the pricing of initial public offerings. Working Paper.

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

Da, Z., Engelberg, J., and Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. *Review of Financial Studies* 28, 1-32.

Das, S. R., and Chen, M. Y. (2007). Yahoo! for Amazon: Sentiment extraction from small talk on the web. *Management Science* 53, 1375-1388.

De Long, J. B., Shleifer, A., Summers, L. H., and Waldmann, R. J. (1990). Noise trader risk in financial markets. *Journal of Political Economy* 98, 703-738.

Edmans, A., Garcia, D., and Norli, Ø. (2007). Sports sentiment and stock returns. *Journal of Finance* 62, 1967-1998.

Fama, E. F., and French, K. R. (2017). International Tests of a Five-Factor Asset Pricing Model. *Journal of Financial Economics* 123, 441–463.

Fernandez-Perez, A., Garel, A., and Indriawan, I. (2020). Music sentiment and stock returns. *Economics Letters*, 109260.

Garcia, D. (2013). Sentiment during recessions. *Journal of Finance* 68, 1267–1300.

Gao, Z., Rhen, H., and Zhang. B., (2020). Googling investor sentiment around the world. *Journal of Financial and Quantitative Analysis* 55, 549-580.

Goetzmann, W. N., Kim, D., Kumar, A., and Wang, Q. (2015). Weather-induced mood, institutional investors, and stock returns. *Review of Financial Studies* 28, 73-111.

Griffin, J. M. (2002). Are the Fama and French factors global or country specific? *Review of Financial Studies* 15, 783–803.

Hirshleifer, D., and Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *Journal of Finance* 58, 1009-1032.

Hirshleifer, D., Jiang, D., and DiGiovanni, Y. M. (2020). Mood beta and seasonalities in stock returns. *Journal of Financial Economics* 137, 272–295.

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

Kamstra, M. J., Kramer, L. A., and Levi, M. D. (2000). Losing sleep at the market: The daylight saving anomaly. *American Economic Review* 90, 1005-1011.

Kamstra, M. J., Kramer, L. A., and Levi, M. D. (2003). Winter blues: A SAD stock market cycle. *American Economic Review* 93, 324-343.

Kamstra, M. J., Kramer, L. A., Levi, M. D., and Wermers, R. (2017). Seasonal asset allocation: Evidence from mutual fund flows. *Journal of Financial and Quantitative Analysis* 52, 71-109.

Kaplanski, G., and Levy, H. (2010). Sentiment and stock prices: The case of aviation disasters. *Journal of Financial Economics* 95, 174-201.

Kumar, A., and Lee, C. M. (2006). Retail investor sentiment and return comovements. *Journal of Finance* 61, 2451-2486.

Lemmon, M., and Portniaguina, E. (2006). Consumer confidence and asset prices: Some empirical evidence. *Review of Financial Studies* 19, 1499-1529.

Loughran, T., and McDonald, B. (2016). Textual analysis in accounting and finance: A survey. *Journal of Accounting Research* 54, 1187-1230.

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

Obaid, K., and Pukthuanthong, K. (2019). A picture is worth a thousand words: Measuring investor sentiment by combining machine learning and photos from news. Working Paper.

Ofek, E., Richardson, M., and Whitelaw, R. F. (2004). Limited arbitrage and short sales restrictions: Evidence from the options markets. *Journal of Financial Economics* 74, 305-342.

Pástor, L., and Vorsatz, M. B. (2020). Mutual fund performance and flows during the COVID-19 crisis. *Review of Asset Pricing Studies* 104, 791-833.

Pontiff, J., (1996). Costly arbitrage: Evidence from closed-end funds. *Quarterly Journal of Economics* 111, 1135–1151.

Saarikallio, S., and Erkkilä, J. (2007). The role of music in adolescents' mood regulation. *Psychology of Music* 35, 88-109.

Shleifer, A., and Vishny, R. W. (1997). The limits of arbitrage. *Journal of Finance* 52, 35-55.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance* 62, 1139-1168.

Thaler, R. H. (1987). Anomalies: Weekend, holiday, turn of the month, and intraday effects. *Journal of Economic Perspectives* 1, 169-177.

Van den Tol, A. J., and Edwards, J. (2013). Exploring a rationale for choosing to listen to sad music when feeling sad. *Psychology of Music* 41, 440-465.

Wang, A. Y., and Young, M. (2020). Terrorist attacks and investor risk preference: Evidence from mutual fund flows. *Journal of Financial Economics* 137, 491-514.

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 August 28, 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 returns. *VOL* is the standard deviation of the daily stock market returns within the week.

Country	*Music Sentiment*	*RET (%)*	*VOL (%)*
Argentina	-0.019	0.138	2.075
Australia	0.006	0.246	0.938
Austria	0.029	0.063	1.211
Belgium	0.027	0.054	0.992
Brazil	0.015	0.131	1.660
Canada	0.047	0.195	0.736
Chile	-0.011	-0.002	1.192
Colombia	0.026	0.077	1.217
Czech	0.047	0.217	0.814
Denmark	0.039	0.383	0.894
Finland	0.020	0.346	0.963
France	0.010	0.206	0.871
Germany	-0.004	0.203	0.926
Greece	-0.008	0.028	1.513
Hong Kong	-0.001	0.153	0.898
Hungary	0.034	0.283	1.247
Iceland	0.032	0.140	0.963
Indonesia	-0.018	0.154	1.170
Ireland	0.030	0.250	1.028
Italy	0.011	0.246	1.063
Japan	0.025	0.149	0.823
Latvia	0.077	0.293	0.900
Malaysia	0.043	0.114	0.611
Mexico	0.012	0.062	1.224
Netherlands	0.036	0.350	0.805
New Zealand	0.007	0.389	0.955
Norway	0.033	0.233	1.080
Panama	0.027	-0.001	0.697
Peru	0.014	0.145	1.145
Philippines	0.004	0.082	1.096
Poland	0.039	0.232	1.226
Portugal	0.004	0.284	0.951
Singapore	0.010	0.139	0.801
Spain	0.010	0.103	0.988
Sweden	0.046	0.293	1.031
Switzerland	0.027	0.352	0.698
Taiwan	-0.008	0.387	0.915
Turkey	0.005	-0.051	1.721
UK	0.024	0.077	0.843
US	0.036	0.330	0.782
Whole sample average	*0.020*	*0.187*	*1.042*
Whole sample SD	*1.183*	*2.680*	*0.694*

Table 2. Validation of our music-based sentiment measure

This table reports the regression estimates of equation (2) from January 1, 2017 to August 28, 2020. The dependent variable, *Music Sentiment,* is weekly change in stream-weighted average valence of the top-200 songs on Spotify. In columns (1), *Positive months* is an indicator variable that equals one in January and March (January and September) for the North Hemisphere (South Hemisphere) countries, and zero otherwise. *Negative months* is an indicator variable that equals one in September and October (March and April) for the North Hemisphere (South Hemisphere) countries, and zero otherwise. In column (2), $\overline{\Delta DCC}$ is the average daily change in deseasonalized cloud cover over the week. Column (3) combines all variables. In columns (1) and (3) regressions include country and year fixed effects. In column (2), the regression includes 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. Table A3 provides the variable definitions. All coefficients are multiplied by 100.

Music Sentiment	(1)		(2)		(3)	
Positive months	0.013	(0.29)			0.014	(0.33)
Negative months	-0.319***	(-7.35)			-0.318***	(-7.31)
$\overline{\Delta DCC}$			-0.158***	(-2.95)	-0.167***	(-2.99)
Fixed Effects	Country, year		Country, month		Country, year	
R^2	0.88%		1.81%		1.03%	
#Obs.	5,890		7,560		5,857	

Table 3. Music sentiment and stock market returns

This table reports the regression estimates from equation (3) over the sample period from January 1, 2017 to August 28, 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 on Spotify for week *t* in a country *i*. 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 ($\overline{\Delta DCC}$). All regressions include country and month fixed effects. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. Constants are not reported. Table A3 provides the variable definitions.

RET (%)	Panel A: Contemporaneous Music Sentiment				Panel B: One-week lagged Music Sentiment			
	(1)		(2)		(3)		(4)	
Music Sentiment	8.285***	(3.27)	7.180***	(3.70)	-16.553***	(-6.34)	-4.655**	(-2.26)
World RET			0.870***	(55.10)			0.868***	(54.60)
VIX			-0.001	(-0.03)			-0.001	(-0.10)
ΔEPU			-0.003***	(-6.51)			-0.003***	(-6.42)
ΔADS			0.021	(0.43)			0.010	(0.20)
$\overline{\Delta DCC}$			0.047	(0.54)			0.037	(0.43)
$RET_{(t-1)}$			-0.037***	(-2.57)			-0.036***	(-2.49)
Fixed Effects	Country, month		Country, month		Country, month		Country, month	
R^2	3.10%		36.71%		3.22%		36.65%	
#Obs.	7,560		7,520		7,560		7,520	

Table 4. Robustness checks

This table reports the regression estimates from equation (3) over the sample period from January 1, 2017 to August 28, 2020. Panel A reports the results of the estimation of Table 3 using local-currency market returns. Panel B reports the regression estimates dropping one country at a time. All regressions include country and month fixed effects. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. Constants are not reported. Table A3 provides the variable definitions.

Panel A: Local-currency market returns

RET (%)	Contemporaneous				One-week lagged			
	(1)		(2)		(3)		(4)	
Music Sentiment	4.599**	(2.13)	5.059***	(2.69)	-10.579***	(-4.72)	-5.525***	(-2.79)
Fixed Effects	Country, month		Country, month		Country, month		Country, month	
Controls	No		Yes		No		Yes	
R^2	2.29%		20.96%		2.43%		20.97%	
#Obs.	7,600		7,520		7,560		7,520	

Panel B: Excluding one country

Excluded country	Contemporaneous				One-week lagged			
	without controls		with controls		without controls		with controls	
Argentina	8.431***	(3.39)	7.048***	(3.70)	-16.565***	(-6.39)	-5.043**	(-2.47)
Australia	8.776***	(3.45)	7.287***	(3.70)	-16.906***	(-6.40)	-4.961**	(-2.37)
Austria	7.624***	(3.01)	6.438***	(3.29)	-16.242***	(-6.20)	-4.289**	(-2.06)
Belgium	8.520***	(3.34)	6.985***	(3.56)	-16.379***	(-6.18)	-4.398**	(-2.10)
Brazil	8.169***	(3.27)	6.635***	(3.48)	-15.963***	(-6.16)	-4.095**	(-2.02)
Canada	8.923***	(3.45)	7.656***	(3.81)	-16.072***	(-5.97)	-4.642**	(-2.17)
Chile	8.220***	(3.27)	7.017***	(3.61)	-16.327***	(-6.24)	-4.433**	(-2.14)
Colombia	8.415***	(3.35)	6.950***	(3.59)	-15.964***	(-6.12)	-4.195**	(-2.03)
Czech	8.641***	(3.37)	7.156***	(3.63)	-16.265***	(-6.12)	-4.226**	(-2.02)
Denmark	8.545***	(3.35)	7.376***	(3.74)	-16.855***	(-6.34)	-5.089**	(-2.42)
Finland	8.383***	(3.28)	7.278***	(3.66)	-16.891***	(-6.33)	-5.071**	(-2.39)
France	9.293***	(3.60)	7.583***	(3.77)	-17.474***	(-6.50)	-4.835**	(-2.25)
Germany	8.139***	(3.19)	6.933***	(3.49)	-16.957***	(-6.40)	-4.923**	(-2.33)
Greece	9.262***	(3.72)	7.902***	(4.15)	-17.375***	(-6.83)	-5.539***	(-2.81)
Hong Kong	8.354***	(3.30)	7.135***	(3.65)	-16.426***	(-6.25)	-4.521**	(-2.18)
Hungary	8.484***	(3.35)	6.975***	(3.59)	-16.480***	(-6.27)	-4.709**	(-2.27)
Iceland	8.730***	(3.32)	6.675***	(3.33)	-16.978***	(-6.22)	-4.463**	(-2.11)
Indonesia	8.824***	(3.50)	7.349***	(3.79)	-16.395***	(-6.26)	-4.800**	(-2.32)
Ireland	8.614***	(3.36)	7.180***	(3.61)	-16.530***	(-6.20)	-4.730**	(-2.23)
Italy	8.095***	(3.16)	6.893***	(3.47)	-16.329***	(-6.13)	-4.286**	(-2.03)
Japan	8.787***	(3.47)	7.251***	(3.71)	-16.866***	(-6.41)	-4.709**	(-2.26)
Latvia	9.360***	(3.57)	7.767***	(3.87)	-17.764***	(-6.53)	-5.584***	(-2.62)
Malaysia	8.593***	(3.38)	7.209***	(3.68)	-16.677***	(-6.31)	-4.750**	(-2.27)
Mexico	8.371***	(3.33)	7.137***	(3.68)	-16.111***	(-6.16)	-4.450**	(-2.15)
Netherlands	8.899***	(3.49)	7.154***	(3.62)	-16.657***	(-6.28)	-4.781**	(-2.27)
New Zealand	8.523***	(3.36)	6.925***	(3.54)	-16.096***	(-6.10)	-4.184**	(-2.01)
Norway	8.696***	(3.44)	7.288***	(3.73)	-15.857***	(-6.03)	-4.007*	(-1.93)
Panama	8.621***	(3.40)	7.390***	(3.77)	-16.266***	(-6.17)	-4.433**	(-2.13)
Peru	8.656***	(3.44)	7.342***	(3.78)	-16.432***	(-6.28)	-4.566**	(-2.21)
Philippines	8.485***	(3.37)	7.085***	(3.65)	-16.277***	(-6.22)	-4.403**	(-2.13)
Poland	9.172***	(3.59)	7.347***	(3.74)	-17.420***	(-6.58)	-5.160**	(-2.46)
Portugal	8.535***	(3.36)	7.428***	(3.77)	-16.437***	(-6.23)	-4.679**	(-2.25)
Singapore	8.447***	(3.34)	7.151***	(3.66)	-16.440***	(-6.26)	-4.661**	(-2.24)
Spain	8.384***	(3.32)	6.907***	(3.54)	-16.245***	(-6.20)	-4.343**	(-2.09)
Sweden	8.489***	(3.32)	7.197***	(3.63)	-16.795***	(-6.31)	-4.888**	(-2.32)
Switzerland	8.947***	(3.46)	7.519***	(3.77)	-17.147***	(-6.38)	-4.955**	(-2.33)
Taiwan	8.575***	(3.38)	7.523***	(3.85)	-16.637***	(-6.32)	-4.903**	(-2.36)
Turkey	7.399***	(2.96)	6.258***	(3.26)	-15.531***	(-5.97)	-3.891*	(-1.91)
UK	8.934***	(3.44)	7.254***	(3.60)	-16.689***	(-6.18)	-4.695**	(-2.18)
US	9.063***	(3.48)	7.662***	(3.75)	-16.618***	(-6.11)	-5.025**	(-2.31)

Table 5. Music sentiment and stock market returns at daily frequency

This table reports the daily regression estimates from equation (3) over the sample period from January 1, 2017 to August 28, 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 on Spotify, lagged by one to five days. 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. Column (1) reports the result of a regression including the five lags of *Music Sentiment*, Columns (2) to (6) show the regression for individual lagged value. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. Constants are not reported. Table A3 provides the variable definitions.

RET_d (%)	(1)		(2)		(3)		(4)		(5)		(6)	
Music Sentiment$_{(d-1)}$	1.883**	(2.04)	1.915**	(2.14)								
Music Sentiment$_{(d-2)}$	0.392	(0.41)			0.132	(0.15)						
Music Sentiment$_{(d-3)}$	-0.241	(-0.26)					-0.3707	(-0.41)				
Music Sentiment$_{(d-4)}$	0.798	(0.86)							1.140	(1.29)		
Music Sentiment$_{(d-5)}$	-2.157**	(-2.32)									-2.447***	(-2.72)
World RET $_{(d+1)}$	-0.022	(-1.63)	-0.022	(-1.59)	-0.022	(-1.61)	-0.022	(-1.61)	-0.022	(-1.61)	-0.022*	(-1.66)
World RET $_{(d)}$	0.857***	(62.50)	0.858***	(62.52)	0.858***	(62.52)	0.857***	(62.53)	0.857***	(62.49)	0.858***	(62.60)
World RET $_{(d-1)}$	0.190***	(17.75)	0.190***	(17.71)	0.190***	(17.68)	0.190***	(17.68)	0.190***	(17.69)	0.190***	(17.69)
RET$_{(d-1)}$	-0.044***	(-5.72)	-0.044***	(-5.72)	-0.044***	(-5.74)	-0.044***	(-5.72)	-0.044***	(-5.71)	-0.044***	(-5.71)
RET$_{(d-2)}$	-0.027***	(-4.01)	-0.027***	(-4.01)	-0.027***	(-4.03)	-0.027***	(-4.04)	-0.027***	(-4.03)	-0.027***	(-4.07)
RET$_{(d-3)}$	-0.004	(-0.64)	-0.004	(-0.63)	-0.004	(-0.62)	-0.004	(-0.62)	-0.004	(-0.63)	-0.004	(-0.65)
RET$_{(d-4)}$	-0.011*	(-1.70)	-0.011*	(-1.69)	-0.011*	(-1.67)	-0.011*	(-1.70)	-0.011*	(-1.72)	-0.011*	(-1.70)
RET$_{(d-5)}$	0.005	(0.74)	0.005	(0.75)	0.005	(0.77)	0.005	(0.75)	0.005	(0.73)	0.005	(0.76)
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	
$\overline{\Delta DCC}$ *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	
Fixed Effects	Country, month, day		Country, month, day		Country, month, day		Country, month, day		Country, month, day		Country, month, day	
R^2	25.55%		25.53%		25.51%		25.51%		25.52%		25.52%	
#Obs.	35,945		36,013		36,013		36,013		36,013		36,013	

Table 6. Effect of music sentiment on stock market returns and limits to arbitrage

This table reports the regression estimates from equation (4) over the sample period from January 1, 2017 to August 28, 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 on Spotify for week *t* in a country *i*. 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 short-selling ban 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. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. Constants are not reported. Table A3 provides the variable definitions. Table A5 provides the start and end periods of short-sale bans during the COVID-19 pandemic by country.

RET (%)	Panel A: Contemporaneous				Panel B: One-week lagged			
	(1)		(2)		(3)		(4)	
Music Sentiment	6.332***	(2.54)	6.533***	(3.38)	-14.019***	(-5.45)	-3.006	(-1.48)
Music Sentiment x BAN	106.541***	(3.80)	33.116*	(1.71)	-121.953***	(-4.46)	-83.025***	(-3.66)
BAN	0.097	(0.25)	-0.267	(-0.85)	0.445	(1.22)	-0.1065	(-0.34)
World RET			0.867***	(54.74)			0.867***	(54.49)
VIX			0.001	(0.23)			0.001	(0.24)
ΔEPU			-0.003***	(-6.46)			-0.003***	(-6.42)
ΔADS			0.031	(0.64)			0.005	(0.11)
$\overline{\Delta DCC}$			0.045	(0.53)			0.038	(0.44)
$RET_{(t-1)}$			-0.037***	(-2.57)			-0.032**	(-2.24)
Fixed Effects	Country, month		Country, month		Country, month		Country, month	
R^2	3.42%		36.76%		3.82%		36.92%	
#Obs.	7,600		7,520		7,560		7,520	

Table 7. Music sentiment and stock market volatility

This table reports the regression estimates from equation (5) over the sample period from January 1, 2017 to August 28, 2020. The dependent variable is the weekly stock market volatility (*VOL*) obtained as the standard deviation of the daily stock market returns 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 on Spotify for week *t* in a country *i*. The control variables are the one-week lagged dependent variable ($VOL_{(t-1)}$), one-week lagged stock market return ($RET_{(t-1)}$), contemporaneous implied volatility (VIX), 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. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. Constants are not reported. Table A3 provides the variable definitions.

VOL (%)	Without Controls (1)		With Controls (2)	
|*Music Sentiment*|	3.836***	(3.67)	1.693**	(2.06)
World RET			-0.049***	(-11.13)
ΔEPU			0.000**	(2.37)
ΔADS			0.008	(0.62)
$\overline{\Delta DCC}$			-0.019	(-0.94)
$VOL_{(t-1)}$			0.464***	(29.00)
$RET_{(t-1)}$			-0.028***	(-7.74)
Fixed Effects	Country, month		Country, month	
R^2	21.48%		41.79%	
#Obs.	7,600		7,520	

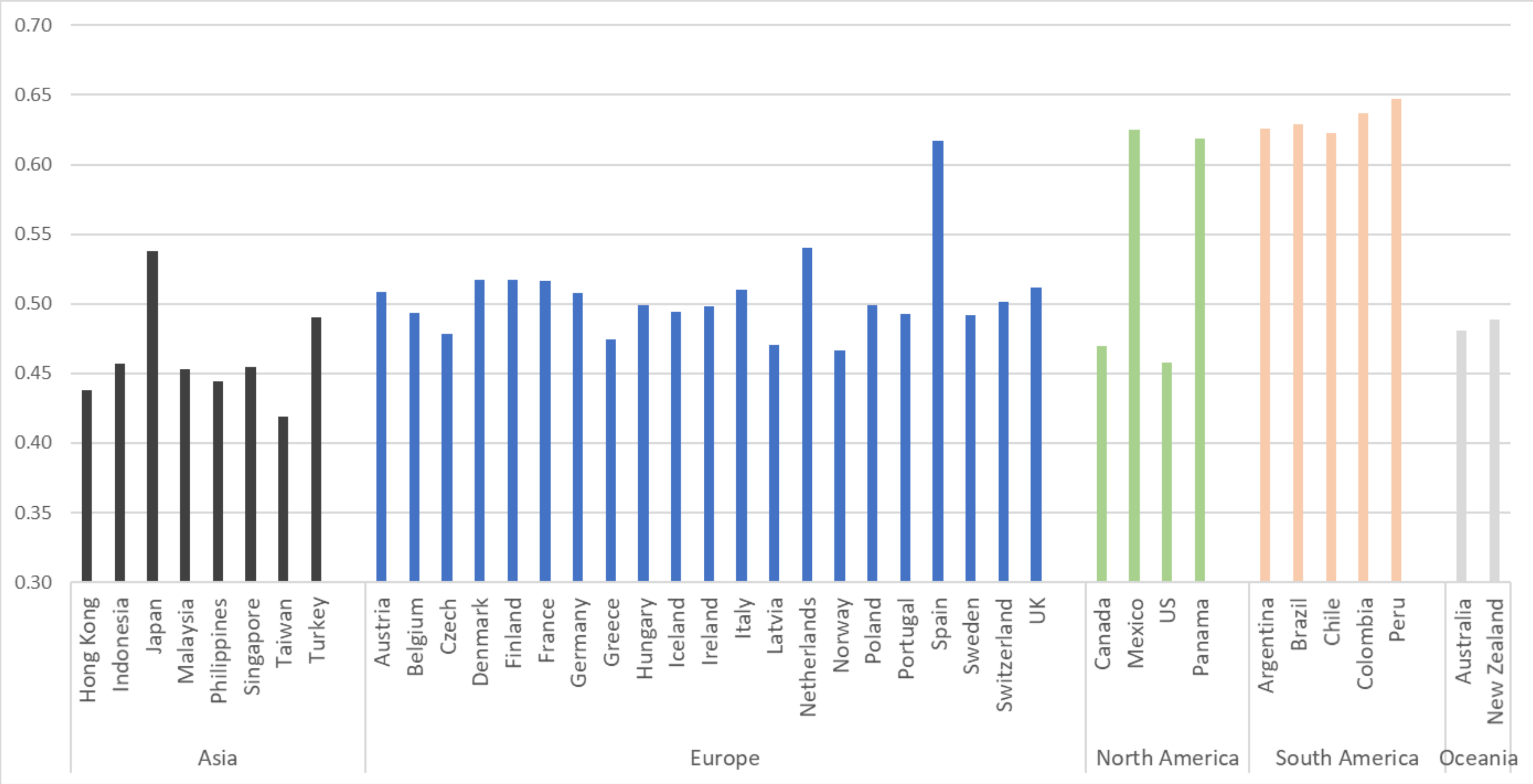
Table 8. Music sentiment and net equity mutual fund flows

This table reports the regression estimates from equation (6) over the sample period from January 1, 2017 to August 28, 2020. The dependent variable is *Net Flows,* the weekly net fund flows scaled by the fund's assets under management in the previous week. The main independent variable is one-week lagged *Music Sentiment*, the weekly change in the stream-weighted average valence of the top-200 songs on Spotify for week *t* in a country *i*. 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. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. Constants are not reported. Table A3 provides the variable definitions.

Net Flows (%)	Without Controls (1)		With Controls (2)	
Music Sentiment$_{(t-1)}$	0.186**	(2.08)	0.228***	(2.57)
World RET			0.768***	(10.28)
VIX			-0.005***	(-26.11)
ΔEPU			0.000***	(-3.39)
ΔADS			0.015***	(7.99)
$\overline{\Delta DCC}$			-0.004	(-0.75)
$RET_{(t-1)}$			0.204***	(3.21)
Net Flows $_{(t-1)}$			0.170***	(21.47)
Fixed Effects	Fund, month		Fund, month	
R^2	0.53%		6.15%	
#Obs.	1,432,005		1,413,496	

Figure 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 August 28, 2020. The 40 countries in our sample are grouped by geographical regions.



Appendix

Table A1: Songs with the highest and lowest valence per country from January 1, 2017 to August 28, 2020

Country	**Songs with highest Valence**			**Songs with lowest Valence**		
	Track.Name	*Artist*	*Valence*	*Track.Name*	*Artist*	*Valence*
Argentina	Dame Tu Mano	El Dipy	0.979	Delicate	Taylor Swift	0.050
Australia	September	Earth, Wind and Fire	0.982	Legion Inoculant	TOOL	0.026
Austria	September	Earth, Wind and Fire	0.982	The arrival | Die Ankunft	Claudius Vlasak	0.031
Belgium	September	Earth, Wind and Fire	0.982	Legion Inoculant	TOOL	0.026
Brazil	Matuto de Verdade	Mano Walter	0.981	Memories	Vintage Culture	0.039
Canada	September	Earth, Wind and Fire	0.982	Legion Inoculant	TOOL	0.026
Chile	Tus Ojos Moreno Vide	Hermanos Morales	0.980	Malagradecido	Mon Laferte	0.039
Colombia	Vispera de Año Nuevo	Guillermo Buitrago	0.989	Delicate	Taylor Swift	0.050
Czech	September	Earth, Wind and Fire	0.982	v korunach stromov	Samey	0.011
Denmark	September	Earth, Wind and Fire	0.982	The Ricochet	Dizzy Mizz Lizzy	0.034
Finland	Pohjoiskarjala	Leevi and the Leavings	0.978	Legion Inoculant	TOOL	0.026
France	September	Earth, Wind and Fire	0.982	The Plan	Travis Scott	0.036
Germany	September	Earth, Wind and Fire	0.982	Rodeo Depatro	awais	0.033
Greece	Running Over	Justin Bieber	0.977	Legion Inoculant	TOOL	0.026
Hong Kong	Running Over	Justin Bieber	0.977	The Plan	Travis Scott	0.036
Hungary	September	Earth, Wind and Fire	0.982	Falling Down	ARTY	0.036
Iceland	September	Earth, Wind and Fire	0.982	Legion Inoculant	TOOL	0.026
Indonesia	There's Nothing Holdin' Me Back	Shawn Mendes	0.969	Pizza	Martin Garrix	0.038
Ireland	September	Earth, Wind and Fire	0.982	0.00	Childish Gambino	0.034
Italy	I Puffi sanno	Cristina D'Avena	0.972	DM	Vegas Jones	0.034
Japan	HACK	Shuta Sueyoshi	0.978	Reflection	Brian Eno	0.031
Latvia	Here Comes Santa Claus	Gene Autry	0.976	Sunrise	Coldplay	0.034
Malaysia	Running Over	Justin Bieber	0.977	The Plan	Travis Scott	0.036
Mexico	September	Earth, Wind and Fire	0.982	Renacer	Zoé	0.049
Netherlands	Hop, Hop, Hop, Paardje In Galop	Noord-Hollands Kinderkoor	0.989	Sunrise	Coldplay	0.034
New Zealand	September	Earth, Wind and Fire	0.982	Legion Inoculant	TOOL	0.026
Norway	September	Earth, Wind and Fire	0.982	Mountaineers (feat. John Grant)	Susanne Sundfør	0.033
Panama	Vive Tu Vida Contento	Héctor Lavoe	0.979	Jaded	Drake	0.037
Peru	Ya Vienen Los Reyes Magos	Villancicos	0.978	Delicate	Taylor Swift	0.050
Philippines	Loving you is so easy	HONNE	0.973	Midnight	Coldplay	0.035
Poland	September	Earth, Wind and Fire	0.982	Legion Inoculant	TOOL	0.026
Portugal	Sempre Bem	Capitão Fausto	0.982	Legion Inoculant	TOOL	0.026
Singapore	Running Over	Justin Bieber	0.977	Colour Spectrum	Coldplay	0.034
Spain	Desamortil	Arnau Griso	0.980	Pizza	Martin Garrix	0.038
Sweden	September	Earth, Wind and Fire	0.982	Bethlehems Stjärna	Cappella Snöstorp	0.035
Switzerland	September	Earth, Wind and Fire	0.982	Ouverture	Faber	0.030
Taiwan	Running Over	Justin Bieber	0.977	The Papers	John Williams	0.031
Turkey	Johnny B. Goode	Chuck Berry	0.969	All That Is or Ever Was or Ever Will Be	Alan Silvestri	0.034
UK	September	Earth, Wind and Fire	0.982	0.00	Childish Gambino	0.034
US	September	Earth, Wind and Fire	0.982	Legion Inoculant	TOOL	0.026

Table A2: MSCI index considered per country

No	Country	MSCI Index (USD)	MSCI Index (local)	No	Country	MSCI Index (USD)	MSCI Index (local)
1	Argentina	MSARGT$	MSARGTL	21	Japan	MSJPAN$	MSJPANL
2	Australia	MSAUST$	MSAUSTL	22	Latvia	RIGSEIN	RIGSEIN
3	Austria	MSASTR$	MSASTRL	23	Malaysia	MSMALF$	MSMALFL
4	Belgium	MSBELG$	MSBELGL	24	Mexico	MSMEXF$	MSMEXFL
5	Brazil	MSBRAZ$	MSBRAZL	25	Netherlands	MSNETH$	MSNETHL
6	Canada	MSCNDA$	MSCNDAL	26	New Zealand	MSNZEA$	MSNZEAL
7	Chile	MSCHIL$	MSCHILL	27	Norway	MSNWAY$	MSNWAYL
8	Colombia	MSCOLM$	MSCOLML	28	Panama	IFFPNM$	IFFMPAL
9	Czech	MSCZCH$	MSCZCHL	29	Peru	MSPERU$	MSPERU$
10	Denmark	MSDNMK$	MSDNMKL	30	Philippines	MSPHLF$	MSPHLFL
11	Finland	MSFIND$	MSFINDL	31	Poland	MSPLND$	MSPLNDL
12	France	MSFRNC$	MSFRNCL	32	Portugal	MSPORD$	MSPORDL
13	Germany	MSGERM$	MSGERML	33	Singapore	MSSING$	MSSINGL
14	Greece	MSGREE$	MSGREEL	34	Spain	MSSPAN$	MSSPANL
15	Hong Kong	MSHGKG$	MSHGKGL	35	Sweden	MSSWDN$	MSSWDNL
16	Hungary	MSHUNG$	MSHUNGL	36	Switzerland	MSSWIT$	MSSWITL
17	Iceland	ICEXALL	ICEXALL	37	Taiwan	MSTAIW$	MSTAIWL
18	Indonesia	MSINDF$	MSINDFL	38	Turkey	MSTURK$	MSTURKL
19	Ireland	MSEIRE$	MSEIREL	39	UK	MSUTDK$	MSUTDKL
20	Italy	MSITAL$	MSITALL	40	US	MSUSAM$	MSUSAML

Table A3: Variables definition and sources

Variable	Description	Source
ADS	U.S. macroeconomic activity index.	Aruoba, Diebold, and Scotti (2009)
BAN	Dummy variable equal to 1 if country's *i* stock market is under short-selling ban at week *t*, and 0 otherwise.	Yale Program on Financial Stability
DCC	Deseasonalized cloud cover	National Oceanic and Atmospheric Administration
EPU	News-based measure of U.S. economic policy uncertainty.	Baker et al. (2016)
Music Sentiment	Total change in the stream-weighted average valence of the top-200 songs individuals of country *i* listen to in week *t*.	Spotify
Net Flows (%)	Weekly net flows of an open-end equity mutual fund, scaled by the fund's assets under management in the previous week.	Morningstar
RET (%)	Weekly return (Friday-end) of the country's stock market index. Index values are in US dollars.	Refinitiv
Valence	The musical positivity conveyed by a song ranging from 0 to 1.	Spotify
VIX	Implied volatility of the S&P 500.	Chicago Mercantile Exchange
VOL (%)	Weekly stock market volatility, measured as the standard deviation of the daily stock market returns within the week.	Refinitiv
World RET (%)	Weekly return of the MSCI World Index, in US dollars.	Refinitiv

Table A4: Music sentiment as a mood proxy at daily frequency

This table reports the regression estimates from the following equation over the sample period from January 1, 2017 to August 28, 2020:

$$Daily\ Music\ Sentiment_{i,d} = \alpha + \sum_{j=1}^{6} \beta_j \cdot Week_{i,j,d} + \theta \cdot \Delta DCC_{i,d} + \varepsilon_{i,d}$$

The dependent variable, *Daily Music Sentiment*, is daily change in stream-weighted average valence of the top-200 songs on Spotify. The controls are the days of the week and the daily change in deseasonalized cloud cover (ΔDCC). All regressions include country and month fixed effects. White-corrected t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. Constants are not reported. Table A3 provides the variable definitions. All coefficients are multiplied by 100.

Daily Music Sentiment$_{(i,d)}$	(1) Calendar-based mood proxy		(2) Calendar-based mood proxy		(3) Calendar-based + Weather-induced mood proxy	
Monday$_{(d)}$	-0.324***	(-35.53)			-0.321***	(-35.33)
Tuesday$_{(d)}$	-0.057***	(-8.49)			-0.057***	(-8.38)
Thursday$_{(d)}$	0.023***	(3.46)			0.022***	(3.27)
Friday$_{(d)}$	0.103***	(10.85)			0.102***	(10.40)
Saturday$_{(d)}$	0.330***	(41.80)			0.330***	(41.55)
Sunday$_{(d)}$	-0.350***	(-43.44)			-0.343***	(-42.56)
$\Delta DCC_{(d)}$			-0.034***	(-13.25)	-0.035***	(-14.77)
Fixed Effects	Country, month		Country, month		Country, month	
R^2	13.84%		0.71%		14.15%	
#Obs.	53,358		52,152		52,152	

Table A5: Short-sale bans in the COVID-19 pandemic

Start and end periods of short-sale bans during the COVID-19 pandemic, from the Yale Program on Financial Stability.

Country	Begin	End
Austria	18/03/2020	18/05/2020
Belgium	16/03/2020	18/05/2020
France	17/03/2020	18/05/2020
Greece	17/03/2020	18/05/2020
Indonesia	02/03/2020	Still in place as of 28/08/2020
Italy	12/03/2020	18/06/2020
Malaysia	23/03/2020	Still in place as of 28/08/2020
Philippines	15/03/2020	16/04/2020
Spain	12/03/2020	18/05/2020
Taiwan	18/03/2020	18/06/2020
Turkey	28/02/2020	Still in place as of 28/08/2020