Music to investor's ears: Can streaming charts predict stock market returns?

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Numa fase complicada do enquadramento internacional em diversos níveis, torna-se mais importante do que nunca olhar em redor e reconhecer aqueles a quem devemos gratidão por tornarem a nossa passagem por este mundo melhor.

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Statement of integrity

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration.

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Música para os ouvidos dos investidores: Podem os charts de streaming prever retornos nos mercados de ações?

Resumo

Ao longo deste estudo, testamos o uso de hábitos de consumo de música e características das canções como um proxy de disposição e, por extensão, do sentimento do investidor.

Começamos por contextualizar a importância de medir o sentimento do investidor de forma a capturar os efeitos da negociação com base em ruído (noise trading), apresentando a literatura teórica enquanto demonstramos exemplos práticos de métodos usados para testar empiricamente estas hipóteses. Específico ao objetivo deste trabalho, prosseguimos com a exposição de estudos que demonstram a relação entre música e a disposição, e como esta influencia – e é influenciada por – sentimento. Fundamentamo-nos em estudos que relacionam sentimento baseado em música com retornos nos mercados financeiros para construir as nossas hipóteses.

Utilizando as tabelas do top 200 semanais do Spotify para 35 países, e valência como uma medida da positividade de cada canção, construímos um indicador semanal de sentimento musical, o Stream-Weighted Average Valence (SWAV). Usamo-lo para testar a ideia de que o sentimento está positivamente correlacionado com os retornos da mesma semana, mas negativamente correlacionado com os retornos da semana seguinte, controlando para a heterogeneidade individual do país e do período. Adicionalmente, também testamos se diferentes características dos ativos são mais suscetíveis a mudanças no sentimento, e o impacto do SWAV na volatilidade do mercado.

Encontramos resultados contraditórios e amiúde inconsistentes. O efeito do SWAV nos retornos do mercado de ações variam consideravelmente com as especificações dos modelos utilizados, e os seus coeficientes são frequentemente estatisticamente insignificantes ou até contrários ao previsto pelas teorias sobre sentimento do investidor. Por outro lado, o índice EPU aparenta ser consistente e significativo na explicação dos retornos dos mercados.

Dados estes resultados, não podemos concluir que o sentimento musical seja um bom proxy para o sentimento do investidor. Terminamos com sugestões para análises futuras neste tópico.

Palavras-Chave: Sentimento do investidor, ruído, música, mercado de ações, retornos

Music to investor’s ears: Can streaming charts predict stock market returns?

Abstract

Over the course of this study, we test the use of music consumption habits and song characteristics as a proxy for mood, and, by extension, investor sentiment.

We begin by providing context for the importance of measuring investor sentiment to capture the effects of noise trading, presenting the existing theoretical literature while showcasing examples of different methods used to empirically test such hypotheses. Specific to the purpose of this study, we move on to research done on the relation between music and mood, and how it influences – and is influenced by – sentiment. We draw from studies connecting music-based sentiment and financial market returns to construct our hypotheses.

Using Spotify’s weekly top 200 streaming charts for 35 countries, and valence as a measure of individual song positiveness, we construct a weekly music sentiment indicator, the Stream-Weighted Average Valence (SWAV). We use it to test the notion that sentiment is positively correlated with same-week stock market returns, but negatively correlated with next-week returns, while controlling for country and time individual heterogeneity. Additionally, we also test if different asset features are more susceptible to changes in sentiment, and the impact of SWAV on market volatility.

We find contradictory and often inconsistent results. The effect of SWAV on stock market returns varies considerably based on model specifications, and its coefficients are frequently statistically insignificant or even contrary to what is predicted by the theory on investor sentiment. On the other hand, Economic Policy Uncertainty index is found to be significant and consistent in predicting stock returns.

Given our results, we cannot conclude music sentiment as SWAV to be a good proxy for investor sentiment. We conclude with suggestions for future research on the topic.

Keywords: Investor sentiment, noise, music, stock market, returns

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ADS	Aruoba-Diebold-Scotti Business Conditions Index
CBOE	Chicago Board Options Exchange
EPU	Economic Policy Uncertainty Index
MSCI	Morgan Stanley Capital International
SWAV	Stream-Weighted Average Valence
VIX	CBOE Volatility Index

1. Introduction

Financial markets are noisy. Noise can be defined as "what makes our observations imperfect" (Black, 1986). It refers to all the pieces of information and events that have the potential to influence how an individual investor may form their expectations, regardless of their origin, veracity or even relevance. Given this, is it reasonable to expect humans who participate in financial markets to be able to individually discern information that should be traded on from what should be discarded? Can we also expect them to be free from bias and other psychological and subjective phenomena when interpreting information? And, if not, can we trust the collective forces in the market to correct those personal biases?

Although several important theories have been built on the assumptions of rational behavior by investors, or that the work of sophisticated traders will compensate for and drive noise traders away from markets, several studies have found sentiment to be a capable factor in the explanation of returns (Baker & Wurgler, 2006; Barber et al., 2009; Yang & Zhou, 2015). More specifically, sentiment can help explain price movements of securities that are more sensitive to irrational trading. Due to limits on the ability of arbitrageurs to correct mispricings, certain stocks, such as small cap and high volatility, are particularly exposed (De Long et al., 1990; Shleifer & Vishny, 1990, 1997).

Which leads to the question on how to measure sentiment, and how to act on it (Zhou, 2018). There are several events and measures that are shown to have some predictive power in the literature. Some are based on trading behavior indicators (Baker & Wurgler, 2006, 2007; Baker et al., 2012; Barber et al., 2009; Yang & Zhou, 2015; Chen et al., 2019), but there are others based on events that do not have an immediate economic justification for their predictive capability: weather conditions (Saunders, 1993; Hirshleifer & Shumway, 2003; Schmittmann et al., 2015; Goetzmann et al., 2015), terrorist attacks (Drakos, 2010), and even the results of sporting matches (Edmans et al., 2007). There are also studies focused on measuring investor sentiment through their web searches (Da et al., 2011, 2015) and social media microblogging (Oliveira et al., 2017).

Recently, some work has drawn from the effects music has on the mood – or, as it is often referred to in the literature, emotion – of individuals (Howarth & Hoffman, 1984; Krumhansl, 1997; Hunter et al., 2011; Yoon et al., 2020). Kaivanto and Zhang (2019) uses a variety of metrics about a track's positiveness to measure sentiment based on what songs are charting. Fernandez-Perez et al. (2020) and Edmans et al. (2021) use a single metric, valence, to compute music sentiment. Valence is defined as "a measure from 0.0 to 1.0 describing the musical positiveness conveyed by a track." by Spotify. Valence, measured for Spotify's top streamed songs, shows promise in its ability to predict returns for stock indices for several countries. In line with the theory, positive sentiment is positively correlated with same week returns, and negatively correlated with following week returns.

The goal of this study is to verify if valence has predictive power over the returns of the stock market, as well as using it to test a few of the notions put forth in the literature on investor sentiment. These are whether it explains small cap stock returns better than large cap stock returns, and if it has any impact in the volatility in the stock market. To do so, we construct an indicator of music sentiment by computing the Stream-Weighted Average Valence (SWAV) for the weekly top 200 Spotify charts, from 2016/12/29 until 2021/12/30, for 35 countries.

What follows is a review of the literature on the topics of investor sentiment and how it fits with theories of efficient financial markets. We explore the theoretical concepts and hypotheses of investor sentiment, how it can be measured, and the possibility of using music-based indicators as a proxy. Afterwards, we will explain the data used to test our hypotheses, as well as the methods employed in doing so. We end by presenting our results and conclusions, as well as the limitations of this study and suggestions for future research.

2. Literature review

2.1. Efficient markets and investor sentiment

In his seminal work, Markowitz (1952) describes portfolio selection as a two-step process. The first is the setting of expectations regarding the performance of individual securities in the future so that the second stage, selecting which securities to include in the portfolio, can take place. This makes return predictability an important goal in the field of Finance. If an investor is able to consistently forecast how asset prices will move with accuracy, that knowledge will allow them to trade accordingly and obtain larger returns.

Markowitz mean-variance model influenced later research, such as Sharpe (1964). Their contributions to research on asset pricing made several critical assumptions about market conditions and how investors make their decisions. This includes rational investors with homogenous expectations and free access to the same (complete) information, who are unable to change asset prices on their own.

However, reality often does not follow those assumptions. For instance, instead of all investors having costless access to the same source of information, they may base their decisions on a multitude of different sources which may not be accessible to all. Their strategies may also be informed by other factors than freely available public information. Black (1986) calls the large number of small individual events that shape how transactions play out as noise. It is argued that, while noise may lead to market imperfection, it is essential for its liquidity, as it leads to more transactions.

Noise can range from imprecise information about a company being shared, to a person deciding to buy stock from a firm because they identify with the brand. Every granular detail that can in any way influence an individual decision on the stock market and does not follow the assumptions of rationality can classify as noise. The existence of traders who act on noise can deviate security prices away from their fundamental values, leading to mispriced assets.

Fama (1965) calls upon "sophisticated traders" as a cleansing force. This group of investors, such as arbitrageurs, seek to identify the intrinsic value of an asset and trade on the assumption that its market price will revert to that in time, if it does not match it at present. In theory, the ability to identify instances of mispriced assets and to act accordingly should help hasten prices to revert to their (perceived) fundamental value by itself. So, while noise traders may pull prices away from the security's intrinsic values (or unintentionally towards it), those individuals with the capacity to exploit such phenomena will revert prices back to equilibrium in their attempts. Eventually, noise traders will lose enough money in financial markets to be driven away.

Yet, some issues may call this notion into question. One is related with the ability of sophisticated traders to identify the fundamental value of securities. Certain assets, such as stocks, are difficult to value correctly, which gives rise to fundamental risk. The harder it is for a stock to be correctly valued, the more likely it is to be constantly mispriced (De Long et al., 1990). Under these circumstances, even sophisticated arbitrageurs may lose on some investments and thus be discouraged from attempting to drive prices back to their equilibrium, potentially aggravating mispricing. Besides this, even when rational investors are able to identify the fundamental value of a security and the associated arbitrage opportunity, they run the risk that noise traders will not revert their expectations for long enough that their positions become unprofitable (Shleifer & Vishny, 1997).

Contrary to the theoretical notion of arbitrageurs, who manage to take up riskless positions and help correct mispricing in doing so, these sophisticated traders do face risk in the form of fundamental risk and persistent noise trader beliefs. Shleifer and Vishny (1990, 1997) and De Long et al. (1990) explain that arbitrageurs may focus on shorter-term, easier to value, less volatile and popular assets, in order to minimize their exposure to said risks. The search for trendy and safe-to-arbitrage assets also creates a snowball effect, where popular assets become ever more attractive (and priced closer to their fundamental value), whereas other types of securities may see their mispricing be aggravated.

There is also the issue that individual investors do not appear to act randomly. Barber et al. (2009) notes how they appear to exhibit systematic behavior patterns. They tend to buy stocks which have performed well in the past, and sell stocks with good recent returns as well, but hold stocks which have provided losses (this is consistent with the disposition effect – the tendencies for risk-aversion in situations of certain wins and risk-seeking behavior in those involving losses – found in prospect theory[1]). Individual investors also buy more stocks when they are experiencing abnormally high trading volumes. All these discoveries point to irrational investors exerting a lot of influence in the pricing of assets, since their decisions are not random and thus limited to the impact a single small investor can have and be quickly offset by another trader with an opposite view. There appear to be commonalities in what noise influences

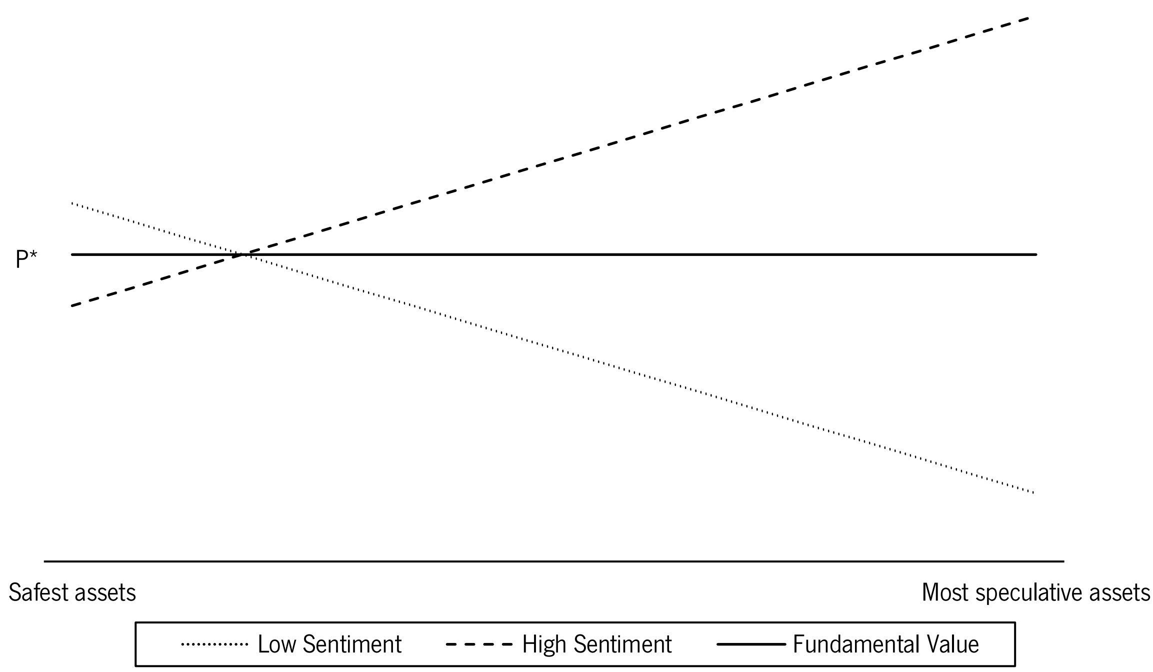
[1] See Kahneman and Tversky (1979), as well as Weber and Camerer (1998).

investors, and how they react to that same information.

The implications are that the beliefs of noise traders do impact prices and returns. It then becomes important to not just understand how to value a security's fundamental value, but also how markets populated by irrational investors will trade on those assets. As Keynes suggested, to understand how the "crowd will behave" in irrational markets may yield better results than sophisticated trading based on fundamental analysis. For that to be possible, there must be a way to identify what constitutes noise significant enough to influence trading decisions, how to measure it, and how such proxies can be used to predict future market movements.

Baker and Wurgler (2006) uses the term sentiment to refer to these irrational beliefs, describing it as the "propensity to speculate". This is because investors with high sentiment are more likely to invest in the type of securities that arbitrageurs are put off by due to the difficulties associated with valuing them, as well as their volatility (high associated idiosyncratic risk). Their sentiment index, comprised of six proxies for sentiment (closed-end stock fund discount, turnover, number of IPOs, returns on IPOs, share of equity issues, and dividend premium), is inversely correlated with next-period returns. When investor

Figure 1: "Sentiment Seesaw": Theoretical mispricing of stocks as a result of sentiment, based on different stock characteristics, from Baker and Wurgler (2007). It represents how the market will value an asset (vertical axis, with P* being its fundamental value) based on how hard it is to arbitrage (horizontal axis)



sentiment is high, demand for speculative stocks increases, which, in turn, diminishes the returns these shares offer in the following period. Inversely, when investors are in low spirits, their demand for riskier stocks decreases, improving their returns in the future.

This relation is illustrated in what Baker and Wurgler (2007) calls the “Sentiment Seesaw” (figure 1). When sentiment is high, investors’ bullishness creates a preference for more speculative stocks, causing them to become overpriced, while safer stocks become underpriced. When investors are bearish, the opposite happens. Either way, the impact of sentiment is not the same on both types of securities: safer stocks, which are easier to arbitrage, are less sensitive to movements in sentiment than speculative stocks.

Regardless, the effect of sentiment appears strong enough that overall returns on the market portfolio are higher in one month when sentiment was lower in the previous period, and vice-versa. This is consistent with previous results on the outperformance of past-losers over past-winners found in De Bondt and Thaler (1985, 1897), which suggested could potentially be attributed to investor overraction, at least in part. Furthermore, this effect is observable across markets. Baker et al. (2012) finds that not only does local sentiment inversely predict local market returns, but so does a global sentiment index. This suggests a degree of sentiment contagion.

2.2. Measuring investor sentiment

Considering these findings, questions about what observable variables and events can be used to accurately measure investor sentiment emerge.

One finding in research is that the weather can influence mood, which could influence decision patterns. For instance, Howarth and Hoffman (1984) establishes a link between hours of sunshine and increased optimism/decreased skepticism on individuals. When applied to financial markets, Hirshleifer and Shumway (2003) found sunshine to be positively and strongly correlated with stock returns. This is in line with a previous study, Saunders (1993), which had provided similar conclusions for the impact of weather in New York City on market indices.

Schmittmann et al. (2015) tests this hypothesis for retail investors (more likely to be less sophisticated and more affected by noise). Firstly, traders purchase more securities on days with good weather, than on days with bad weather. Secondly, they buy riskier securities (and sold safer ones) on days with good weather. This is in congruence with the findings that individuals are more optimistic and less skeptical under certain weather. Lastly, they were more active on days with bad weather, indicating the possibility of an opportunity cost of trading when meteorological conditions are good.

The implications of local weather being a potential factor in explaining market returns are substantial. And these discoveries are not limited to small, individual, irrational, and unsophisticated traders. According to Goetzmann et al. (2015), the influence of weather on institutional investors follows the same logic and patterns as it does in retail investors, with apparent practical effects on returns as well (it could be argued this finding could already be extrapolated from Saunders (1993), due to the status of New York City as a major financial market).

There are other findings in the literature. Edmans et al. (2007) notes how the results of international football (and other sports, to a lesser extent) matches can influence stock market results by negatively impacting the mood of local investors in the case of a loss. This finding was stronger for countries with higher affinity for the sport and for smaller stocks. Drakos (2010) studies the effect terrorist attacks have on stock markets, and draws similar conclusions. But these are examples of events that affect mood, and not the other way around. If we assume this to be a three-step process, where an instance of noise impacts investor sentiment, which in turn influences their decisions and, ultimately, their returns, then these studies can be considered to be focusing on measuring the impact of the initial event (figure 2).

Figure 2: Conceptualization of the impact of noise on sentiment and financial markets

There are, however, studies that focus on more direct measures of investor sentiment. Da et al. (2011) uses internet search queries for listed companies on Google to find that higher search frequency is associated with higher stock prices for the first two weeks, with an eventual reversal occurring later on. It was associated with better first-day returns and long-term underperformance of IPOs. It also demonstrates that higher search frequency is related with more trading from retail investors, mirroring the previously discussed results. Da et al. (2015) FEARS shows how negative search queries, such as "recession" or "bankruptcy", predict lower immediate returns and higher subsequent returns. Furthermore, it also predicts flows from mutual equity funds to bond funds.

There is also evidence of microblogging being a useful measure of investor sentiment. Oliveira et al. (2017) finds Twitter post contents and volume (related to stock market discussions via the usage of cashtags) to be suitable predictors of stock returns. The main advantage of using social media to measure sentiment is its widespread usage and virtually immediate availability. A post can be added to measure sentiment as soon as it goes live. Oliveira et al. (2017) differs from Da et al. (2011, 2015) in that social media posts not only reflect the sentiment of who is posting, but can also influence the sentiment of who is interacting with the post, just how it is conceptualized in figure 2. Each post can provide insight into the mood of the poster, influenced by outside factors acting as noise, while it also acts as noise itself, informing the mood and outlooks of others, thus combining elements of the first type of studies (into the events that can alter sentiment) and the second (direct measures of investor mood).

The same logic can be applied to music sentiment measures.

2.3. Music, mood and markets

On the one hand, music appears to influence mood. Krumhansl (1997) noted that music meant to convey different emotions introduced different physiological changes in listeners. Listening to a "happy" song will affect individuals differently than listening to a "sad" one. Chart topping music can, therefore, be a factor of influence in the mood of a great number of individuals. On the other hand, current mood might also define what music a person might want to listen to. An example of this is that individuals experiencing sentiments of sadness exhibit a preference for music matching their mood (Hunter et al., 2011; Yoon et al., 2020). Thus, it can be argued that a when music charts are dominated by positive music, it will be both a reflex of general sentiment among the populace and a factor of noise influencing mood as well.

Kaivanto and Zhang (2019) utilizes lyrics and a variety of musical characteristics (based on Spotify's Developer API metrics) from top-charts songs to produce a sentiment measure for the US and UK. This indicator was close to the Baker-Wurgler sentiment index in predictive power, under certain conditions, and outperformed the Michigan Index of Consumer Sentiment (survey based).

However, Edmans et al. (2021) point to the concerns over the inclusion of measures based on lyrics. Not only can there be problems inherent to textual analysis, but there are also issues of positive sounding songs having lyrics associated with negative feelings. Additionally, it makes measuring music-sentiment of songs in different languages more difficult. Thus, the study focuses only on the usage of valence, Spotify's metric for a song's positiveness, of chart-topping tracks (on Spotify) to construct their measure of investor sentiment based on popular music consumptions.

It builds on the work put forth by Fernandez-Perez et al. (2020), which found music sentiment to reflect the effects of other noise inducing events (such as holidays and post-holidays, weather, or day of the week). Based on daily data, this measure is associated with price reversals from the day after and up to a week later, with the results being stronger for stocks that are harder to arbitrage (small cap, high beta and low liquidity stocks). Edmans et al. (2021), which shifts to weekly data, also shows that music sentiment is positively related to concurrent week returns and negatively correlated with following week returns, and it manages to predict increases in mutual funds inflows. Furthermore, absolute weekly changes in music sentiment predict increases in market volatility.

These results lead to the conclusion that an investor sentiment index based on music listening habits of the general public may be capable of capturing wider effects of mood, and thus predict how irrational investors will choose to trade.

3. Data

3.1. Music sentiment

With over 406 million users (of which 180 million are paying subscribers)[2], Spotify is the world's largest music streaming platform (Porter, 2022). Its status as market leader gives Spotify the advantage of capturing the music listening habits and tastes of a large portion of the population through its collection of user data, and its top 200 weekly charts for each country its service is available on acts as an easily comparable measure. The charts provide information on the most listened to songs and how many times each was streamed, for each week ending on a Thursday, since the week ending on the 29th of December, 2016.

In addition to data on the most streamed songs, Spotify also computes several song characteristics. Among those is valence, described by Spotify as a measure of "musical positiveness"[3]. For each song, Spotify computes valence as a measure between 0 and 1, where the closer to 1 a song's *valence* is, the more positive it sounds, while the closer to 0 the more negative.

Using Spotify's data, it is possible to create a measure of music sentiment for a country by computing the average valence for a given week's top 200 charts[4]. The average will be weighted by the number of times each song gets streamed that week, so that the more popular tracks will have more impact in shaping sentiment. The result is the stream-weighted average valence (SWAV), given by the expression

$$SWAV_{c,t} = \sum_{i=1}^{200} \frac{streams_{i,c,t}}{\sum_{i=1}^{200} streams_{i,c,t}} \times valence_{i,c,t} \quad (1)$$

[2] Latest available data as of the 17th of February, 2022. See Bursztynsky (2022).

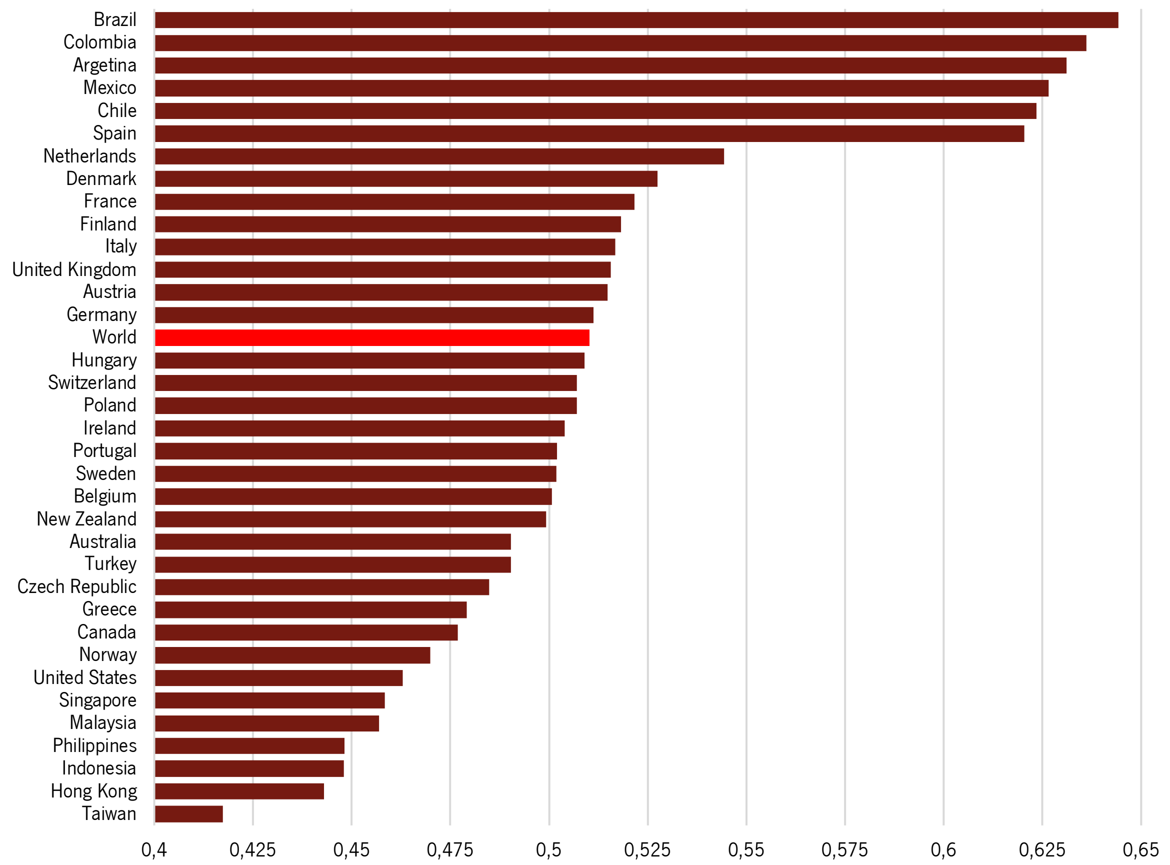
[3] More information on *valence*, as well as other audio features computed by Spotify, see https://developer.spotify.com/documentation/web-api/reference/#/operations/get-several-audio-features

[4] It is important to note that, while rare, there are instances of available weekly charts not featuring 200 songs. Even more uncommon, but present still, is the existence of songs which, while featured in the charts, do not have data on valence available.

where $SWAV_{c,t}$ is the stream-weighted average valence for country c in week t, $streams_{i,c,t}$ is the number of streams of song number i in the top 200 chart of country c in week t, and $valence_i$ is the valence of that same track, as proposed in Edmans et al. (2021). SWAV will, just like valence, be a measure between 0 and 1, where the closer to 1 it is, the more positive the music tastes of a country.

For computing SWAV, the top 200 weekly charts from 35 countries (see figure 3 for the full list), as well as one for the entire world, starting on the week ending on 29th of December of 2016, up until the week ending on the 30th of December of 2021, for a full 262 weekly charts per country (only countries with charts available uninterruptedly for that full period were considered)[5]. After collecting data on the weekly charts, the ID (Spotify's way of identifying each unique track) of every individual song featured in any chart was used to retrieve its valence directly from Spotify's API[6]. The result is a total of 61 296 unique tracks for which valence was available.

Figure 3: Average SWAV, by country, from 2016-12-29 to 2021-12-30



[5] The charts are made available on https://spotifycharts.com/home/

[6] The data on *valence* can be retrieve using https://developer.spotify.com/console/get-audio-features-several-tracks/

However, music sentiment will not be given by SWAV, but by weekly changes in SWAV. This sidesteps the inherent differences between each country's music listening habits illustrated by figure 3, and better captures what is intended by a measure of investor sentiment: mood changes. So, sentiment will be high not when SWAV is high, but when changes from one week to the next are positive. It will be computed using the formula

$$\Delta SWAV_{c,t} = SWAV_{c,t} - SWAV_{c,t-1} \qquad (2)$$

When ΔSWAV is positive, it means that the most popular songs in that week sounded more positive than in the week before. If the hypothesis put forward in the literature are correct, one would expect higher ΔSWAV to mean more positive sentiment among Spotify users (who opt for more positive sounding tracks as a result of their mood, or who see their mood positively affected by the songs popular around them).

3.2. Stock market returns

In order to estimate the impact of music sentiment in the stock market, a stock market index is also required. Similar to Edmans et al. (2021), the chosen index is the MSCI Index. More specifically, the daily MSCI Total Return Index, retrieved from Refinitiv[7].

The advantages of using MSCI Total Return Index are, firstly, it being available for a large number of countries, thus constituting an index which is easily comparable across several markets, since the same methodology applies for each one. Secondly, the fact it can be computed for each market in USD, which again helps make the indices more comparable.

Stock market returns are calculated as the weekly log returns of this index, for each country, by using each the index for each Thursday (or, when unavailable, the last trading day before that). Besides log returns, volatility is also measured as the standard deviation of the MSCI Total Return Index over the course of that same week.

[7] The methodology employed by MSCI is detailed in https://www.msci.com/eqb/methodology/meth_docs/MSCI_IndexCalcMethodology_Feb2022.pdf

There is yet another advantage of using MSCI Total Return Index as the stock market index: MSCI computes the index not just for the overall market, but also for small cap and large cap stock individually. This benefit allows for the testing of the investor sentiment theory of less popular, harder to arbitrage assets (in this case small cap stock) being more susceptible to noise than the stock of bigger corporations.

3.3. Control variables

Besides music sentiment, other control variables will be added in order to further test our hypothesis.

One is the Economic Policy Uncertainty (EPU), as proposed by Baker et al. (2016). It aims to measure uncertainty on a daily basis (for the United States only) by turning to Newsbank's newspaper coverage to find articles featuring a at least one term (or variants) of three categories:

1. "uncertainty" or "uncertain";
2. "economic" or "economy";
3. "Congress", "deficit", "Federal Reserve", "legislation", "regulation" or "White House".

The daily measure of EPU was downloaded from Professors Baker, Bloom and Davis' website[8], which was then averaged for each week ending on a Thursday. Nevertheless, like it was the case with SWAV, EPU was taken for its weekly (this time relative) changes, not its absolute weekly value.

The CBOE Volatility Index (VIX) also tries to capture investor sentiment by way of forward-looking volatility. It does so by deriving its measure from the prices of options on the S&P 500 Index with near expiration dates, in order to compute a real-time prediction of volatility in the following 30 days. Just like with EPU, instead of taking the absolute VIX value, we get the daily closing VIX value[9], choose the one for every Thursday, and compute relative changes from one week to the next.

The last control variable is the business conditions measurement proposed by Aruoba et al. (2009), where the authors attempt to measure economic activity at a high frequency by using several indicators, such as seasonally adjusted initial jobless claims or difference between the 10-year and 3-month US

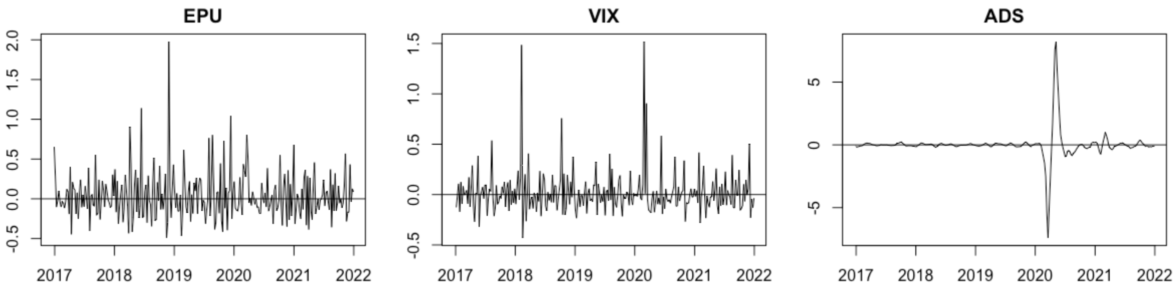
[8] The daily data is available at https://www.policyuncertainty.com/us_monthly.html

[9] Historical daily data available at https://www.cboe.com/tradable_products/vix/vix_historical_data/

Treasury yields. ADS provides a daily measure of the health of the economy (for the United States), and thus controls for the impact of the macroeconomic context and events on the stock market. Daily ADS was taken from the Philadelphia Federal Reserve website[10] and selected for every Thursday, yet this time, like with music sentiment, weekly changes are not relative.

The time series for all control variables is shown in figure 4.

Figure 4: Weekly changes in the control variables (EPU, VIX and ADS). EPU and VIX are computed as relative changes, while ADS is computed as nominal changes.



[10] Available at https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/ads

4. Methodology

4.1. Stock returns and music sentiment

In order to test our hypotheses, a regression analysis will be employed, with the dependent variable being stock market returns (MSCI Total Return Index), and contemporaneous music sentiment as the explanatory variable. The basic model is thus given by the expression

$$R_{c,t} = \beta_1 \Delta SWAV_{c,t} + \varepsilon_{c,t} \tag{3}$$

where $R_{c,t}$ is the weekly log returns of the MSCI Total Return Index of country c in week t, $\Delta SWAV_{c,t}$ is music sentiment of country c in week t, and $\varepsilon_{c,t}$ is the residual term.

Then, the control variables will be added. Besides the ones discussed before (ΔEPU, ΔVIX and ΔADS), a couple more will be introduced. One is lagged stock market returns, to control for any potential autocorrelation. The other is the MSCI Total Return Index for the entire world, which allows to control for the impact of worldwide trends and events in each market's stock returns, which should not be attributed to local investor sentiment. With these two added variables, the model becomes

$$R_{c,t} = \beta_1 \Delta SWAV_{c,t} + \beta_2 R_{c,t-1} + \beta_3 R_{world,t} + \varepsilon_{c,t} \tag{4}$$

where $R_{c,t-1}$ is simply the one week lagged returns, and $R_{world,t}$ is the log returns on the world's MSCI Total Return Index. Finally, the other measures of sentiment/uncertainty presented in the literature will be added, resulting in a complete model given by the expression

$$\begin{gathered} R_{c,t} = \beta_1 \Delta SWAV_{c,t} + \beta_2 R_{c,t-1} + \beta_3 R_{world,t} + \\ + \beta_4 \Delta EPU_t + \beta_5 \Delta VIX_t + \beta_6 \Delta ADS_t + \varepsilon_{c,t} \end{gathered} \tag{5}$$

In order to further test if music sentiment captures some of the main concepts of investor sentiment theory, it is important to not test contemporaneous music sentiment exclusively. As such, lagged music sentiment will also be used, replacing same week sentiment ($\Delta SWAV_{c,t-1}$ instead of $\Delta SWAV_{c,t}$) and as an addition to the existing models (4), (5), and (6). If music sentiment holds true to the theory, it is expected that contemporaneous SWAV will be found to be positively correlated with stock market returns, while lagged SWAV will be negatively correlated, in accordance with the concept of irrational expectations and subsequent price reversals.

Since we will be dealing with panel data, a fixed effects model will be used in the analysis. Besides the variables described above, factors will also be included to handle inherent differences between countries and time. Whereas Edmans et al. (2021) uses month as the only time factor, we will test for using month, year and month, and individual weeks, when doing so does not cause multicollinearity issues.

To deal with outliers, all variables will be winsorized at the 2,5% and 97,5% level, for each country individually, so as to still retain international differences.

4.2. Stock characteristics

To test the hypothesis regarding investor sentiment affecting asset types differently, it is necessary to rethread the same models, this time altering the explained variable to reflect it. As discussed before, MSCI Total Return Index is available for small cap and large cap stocks. Thus, the same methods as before will be used, for small stock returns and large cap returns, and the results compared. By doing so, we can check for differences in the coefficients and the explanatory power of music sentiment for different stock characteristics.

Based on the literature, we expect music sentiment to be more relevant in explaining returns on small cap stock than for the regular index, and for large cap stock to be the least affected by changes in SWAV. This is in relation with the theory put forward in Baker and Wurgler (2007), with the "Sentiment Seesaw". Small cap stock should be harder to correctly price and, due to less popularity, harder-to-arbitrage, than large cap stock, leading to it being more sensitive to noise and the sentiment of investors.

4.3. Stock market volatility

Another potential impact of music sentiment is on stock market volatility. When there are shocks to sentiment, the impact on trading (and thus stock prices) should be larger the greater the shock. In order to test this hypothesis, another model will be employed, by altering the previous ones. It is given by

$$Vol_{c,t} = \beta_1 \left| \Delta SWAV_{c,t} \right| + \beta_2 sign_{c,t} + \varepsilon_{c,t} \tag{6}$$

where $Vol_{c,t}$ is the computed weekly volatility for the daily MSCI Total Return Index for country c in week t, and $\left|\Delta SWAV_{c,t}\right|$ is the absolute change in music sentiment for country c in week t, and $sign_{c,t}$ is a dummy variable equal to 1 when the weekly change in SWAV is negative. The bigger the change in music sentiment, the greater the expected impact on stock returns (both negative and positive). The inclusion of a dummy variable denoting the sign of the change has to do with the expectation that negative changes in sentiment are more impactful than positive ones.

The previously mentioned control variables will be added once again, with the exception of VIX, since it is itself a measure of volatility, and the addition of a lag for volatility. Like before, the analysis will be performed for both contemporaneous and lagged music sentiment, and the impact of changing the time factors will be taken into account. The complete model (excluding country and time factors), will be

$$\begin{gathered} Vol_{c,t} = \beta_1 \left| \Delta SWAV_{c,t} \right| + \beta_2 sign_{c,t} + \beta_3 R_{c,t-1} + \beta_4 R_{world,t} + \\ + \beta_5 \Delta EPU_t + \beta_6 \Delta ADS_t + \beta_7 Vol_{c,t-1} + \varepsilon_{c,t} \end{gathered} \tag{7}$$

5. Results

5.1. Impact of music sentiment on stock market returns

We first begin by running the basic model. We do so by testing it using the three different time factors consecutively, for contemporaneous and one week lagged music sentiment.

Table 1: Regression results for models (3), changing the time factor. The dependent variable is weekly log returns of the MSCI Total Return Index (in %). White-corrected t-test statistics in parenthesis. The 10%, 5% and 1% significant levels are represented by *, **, and ***, respectively.

	Same week music sentiment						Lagged music sentiment					
	(3)		(3)		(3)		(3)		(3)		(3)	
$\Delta SWAV_t$	0,866	(0,329)	-18,533	(-6,735)***	-20,162	(-7,242)***						
$\Delta SWAV_{t-1}$							-1,736	(-0,662)	8,341	(3,075)***	6,710	(2,410)**
Factors	Country, Week		Country, YearMonth		Country, Month		Country, Week		Country, YearMonth		Country, Month	
Adj. R^2	0,467		0,121		0,030		0,466		0,116		0,024	
Obs	9133		9133		9133		9098		9098		9098	
df	8837		9038		9086		8803		9003		9051	

The results obtained already raise some concerns. Firstly, the models have issues regarding heteroscedasticity (White-corrected standard errors were used to compute t-statistics). However, and more importantly, changing the time factor completely alters the results. When employing the week to control for factors exogenous to the model but intrinsic to that period of time (individual heterogeneity), just as we do for each country, the estimated coefficients match the theory: music sentiment is positively correlated with same week returns, but negatively correlated with next week returns. Nevertheless, they are not statistically significant.

However, when using only the month – similarly to Edmans et al. (2021) – or year and month, the results become statistically significant, but completely contrary not just to what they were before, but to what would be expected if SWAV was an appropriate measure of investor sentiment. The model's explanatory power also drops significantly, though that is not surprising considering the loss in the ability of capturing as many exogenous factors specific to each time period.

The most pressing issue regarding these differences is the inability to add any control variables other than lagged returns while using week as the fixed factor, due to problems of perfect multicollinearity. Since world returns, EPU, VIX and ADS do not vary by country, including a time factor at the week level will make them perfectly correlated with the week they were computed for, since each weekly observation would be the same for all countries. Thus, even if the model specification using a weekly time factor is the only one with results consistent with the literature (despite not being statistically significant), we shall proceed by using the two other variations of the models.

Table 2: Regression results for models (3), (4) and (5). The dependent variable is weekly log returns of the MSCI Total Return Index (in %). White-corrected t-test statistics in parenthesis. The 10%, 5% and 1% significant levels are represented by *, **, and ***, respectively.

	Same week music sentiment						Lagged music sentiment					
	(3)		(4)		(5)		(3)		(4)		(5)	
$\Delta SWAV_t$	-20,162	(-7,242)***	-3,882	(-1,819)*	-4,224	(-1,974)*						
$\Delta SWAV_{t-1}$							6,710	(2,410)**	4,814	(2,233)**	5,094	(2.360) **
R_{t-1}			-0,010	(-0,845)	-0,013	(-1,044)			-0,010	(-0,836)	-0,013	(-1,064)
R_{world}			1,041	(62,825)***	1,043	(41,108)***			1,042	(62,880)***	1,046	(41,136)***
ΔEPU					-0,326	(-3,642)***					-0,342	(-3,817) ***
ΔVIX					-0,018	(-0,071)					0,011	(0,043)
ΔADS					0,016	(0,204)					0,030	(0,365)
Factors	Country, Month		Country, Month		Country, Month		Country, Month		Country, Month		Country, Month	
Adj. R^2	0,030		0,379		0,380		0,024		0,378		0,379	
Obs	9133		9131		9131		9099		9096		9096	
df	9086		9082		9079		9051		9047		9044	

When doing so, SWAV is found to be a statistically significant variable in explaining stock returns. Yet, it does so in contrast to what is predicted by the theory. Contemporaneous music sentiment is still negatively correlated with stock market returns, whereas one week lagged sentiment is positively correlated with next week returns. While same week and lagged sentiment coefficients having different signs is consistent with the theory on price reversal, the relation should be inversed.

Adding both contemporaneous and lagged SWAV to the same regression does little to alter results. The only meaningful change is once again related to how using different time factors can impact results, leading to fluctuations in the statistical significance of several variables.

Table 3: Regression results for models (3) and (5) using both same week and lagged music sentiment, for different time factors. The dependent variable is weekly log returns of the MSCI Total Return Index (in %). White-corrected t-test statistics in parenthesis. The 10%, 5% and 1% significant levels are represented by *, **, and ***, respectively.

	(3)		(5)		(3)		(5)	
$\Delta SWAV_t$	-19,281	(-6,779)***	-3,407	(-1,562)	-17,157	(-6,068)***	-4,281	(-1,928)*
$\Delta SWAV_{t-1}$	4,276	(1,504)	4,672	(2,130)**	5,688	(2,043)**	2,619	(1,193)
R_{t-1}			-0,013	(-1,040)			-0,038	(-3,104)***
R_{world}			1,044	(41,090)***			1,024	(37,298)***
ΔEPU			-0,347	(-3,867)***			-0,299	(-3,166)***
ΔVIX			0,009	(0,035)			0,177	(0,696)
ΔADS			0,024	(0,295)			0,094	(0,630)
Factors	Country, Month		Country, Month		Country, YearMonth		Country, YearMonth	
Adj. R^2	0,029		0,379		0,119		0,400	
Obs	9098		9096		9098		9096	
df	9050		9043		9002		8995	

Although this study already tries to capture idiosyncratic nature of a month, whether in general or in a given year in particular, by including a fixed effect for time, this raises the issue of the characteristics of each month not being the same in every country. While some traits stay the same for every country, others, such as the passing of seasons, do not. Adding two dummy variables to identify for typically more positive (January and March in the Northern Hemisphere, January and September in the Southern Hemisphere) and negative months (September and October in the Northern Hemisphere, March and April in the Southern Hemisphere), similarly to Edmans et al. (2021), however, does not alter the results (see table 14).

When using different specifications and factors, the statistical significance of music sentiment changes enough to be inconsistent. With these results, it becomes difficult to declare music sentiment as computed in this fashion, as a good predictor of stock market returns.

5.2. Small cap and large cap stock

When performing the analysis for the small cap and large cap indices individually, the same conclusions as before arise.

Using the week as the fixed factor, music sentiment is not statistically significant for the normal model or the large cap model. However, the theory once again holds, with same week sentiment having a positive coefficient, while the lagged sentiment coefficient is estimated to be negative. Additionally, the concept of sentiment affecting assets differently, with smaller stock being the most impacted by noise, and thus sentiment, is also validated. The small cap stock returns present a higher R^2, while also having lagged sentiment be statistically significant, while large cap returns model present a lower explanatory power. The only inconsistency is with how same-week SWAV is not as significant in the small cap model as it is in the all cap one, though the disparity is not substantial.

Table 4: Regression results for model (3) using both same week and lagged music sentiment. The dependent variables are weekly log returns of the MSCI Total Return Index (in %) in panel (A), weekly log returns of the MSCI Total Return Index for small cap stock (in %) in panel (B), and weekly log returns of the MSCI Total Return Index for large cap stock (in %) in panel (C). White-corrected t-test statistics in parenthesis. The 10%, 5% and 1% significant levels are represented by *, **, and ***, respectively.

	All Cap		Small Cap		Large Cap	
	(A)		(B)		(C)	
$\Delta SWAV_t$	0,819	(0,308)	0,698	(0,252)	0,142	(0,048)
$\Delta SWAV_{t-1}$	-1,660	(-0,630)	-8,233	(-2,980)***	-0,411	(-0,138)
Factors	Country, Week		Country, Week		Country, Week	
Adj. R^2	0,466		0,483		0,408	
Obs	9098		9093		8782	
df	8802		8797		8486	

When moving to month as the time fixed factor in order to add the control variables, the models once again contradict expectations. The signs of both same week and lagged SWAV defy the theory and the previous results, while only being simultaneously significant in the large cap model. Small cap returns, which were supposed to be the most affected by noise trading, are the impacted by music sentiment the least.

Table 5: Regression results for model (5) using both same week and lagged music sentiment. The dependent variable is weekly log returns of the MSCI Total Return Index (in %) in panel (A), weekly log returns of the MSCI Total Return Index for small cap stock (in %) in panel (B), and weekly log returns of the MSCI Total Return Index for large cap stock (in %) in panel (C). White-corrected t-test statistics in parenthesis. The 10%, 5% and 1% significant levels are represented by *, **, and ***, respectively.

	All Cap		Small Cap		Large Cap	
	(A)		(B)		(C)	
$\Delta SWAV_t$	-3,407	(-1,562)	-1,007	(-0,441)	-5,134	(-2,099)**
$\Delta SWAV_{t-1}$	4,672	(2,130)**	0,718	(0,309)	6,487	(2,597)***
R_{t-1}	-0,013	(-1,040)	0,001	(0,139)	-0,007	(-0,566)
R_{world}	1,044	(41,090)***	1,092	(42,101)***	1,017	(35,711)***
ΔEPU	-0,347	(-3,867)***	-0,248	(-2,741)***	-0,425	(-4,219)***
ΔVIX	0,009	(0,035)	0,095	(0,371)	-0,157	(-0,560)
ΔADS	0,024	(0,295)	0,047	(0,554)	-0,016	(-0,163)
Factors	Country, Month		Country, Month		Country, Month	
Adj. R^2	0,379		0,389		0,328	
Obs	9096		9091		8777	
df	9043		9038		8724	

Just as before, music sentiment behaves unpredictably. When using a single model specification, the results are as expected. When altering the time factor in order to include other control variables, however, the findings are contrary to what was anticipated. Not only are the signs of the coefficients reversed to the theory, but the relation of the differences found between the coefficients in the all cap, small cap, and large cap stock returns models are as well.

5.3. Music sentiment and volatility

Regarding the impact of changes in music sentiment in the stock market volatility, our results once again show music sentiment to be highly sensitive to different model specifications. This time, however, it is while using a weekly time factor that sentiment breaks from the theory, by having absolute weekly changes be negatively correlated with market volatility. When using year and month, or month, as the time factor, contemporaneous music sentiment behaves as predicted, even being statistically significant in the latter case. Lagged SWAV is also inconsistent, varying significantly based on which factor is being used, and is not found to be significant in explaining volatility in any case.

Table 6: Regression results for model (6) using same-week and lagged music sentiment separately, for different time factors. The dependent variable is weekly volatility of the MSCI Total Return Index's log returns (in %). White-corrected t-test statistics in parenthesis. The 10%, 5% and 1% significant levels are represented by *, **, and ***, respectively.

	Same week music sentiment						Lagged music sentiment					
	(6)		(6)		(6)		(6)		(6)		(6)	
$\lvert\Delta SWAV_t\rvert$	-0,734	(-0,863)	0,068	(0,084)	2,421	(2,445)**						
$sign_t$	0,017	(1,454)	0,014	(1,213)	0,006	(0,440)						
$\lvert\Delta SWAV_{t-1}\rvert$							-1,130	(-1,360)	-0,490	(-0,614)	1,348	(1,371)
$sign_{t-1}$							0,000	(0,041)	0,000	(0,023)	-0,006	(-0,416)
Factors	Country, Week		Country, YearMonth		Country, Month		Country, Week		Country, YearMonth		Country, Month	
Adj. R^2	0,871		0,848		0,774		0,871		0,848		0,774	
Obs	9129		9129		9129		9094		9094		9094	
df	8832		9033		9081		8798		8998		9046	

Regarding the hypothesis of there being a difference between positive and negative sentiment, no evidence is found to support such theory. The dummy variables used to capture this effect are not found to be statistically significant, and are also sensitive to different models.

Table 7: Regression results for models (6) and (7) using both same week and lagged music sentiment, for different time factors. The dependent variable is weekly volatility of the MSCI Total Return Index's log returns (in %). White-corrected t-test statistics in parenthesis. The 10%, 5% and 1% significant levels are represented by *, **, and ***, respectively.

	(6)		(7)		(6)		(7)	
$\lvert\Delta SWAV_t\rvert$	2,281	(2,283)**	1,579	(1,809)*	0,064	(0,079)	0,192	(0,245)
$sign_t$	0,006	(0,412)	0,004	(0,361)	0,013	(1,146)	0,011	(1,029)
$\lvert\Delta SWAV_{t-1}\rvert$	1,084	(1,097)	0,395	(0,462)	-0,477	(-0,597)	-0,124	(-0,160)
$sign_{t-1}$	-0,006	(-0,418)	0,002	(0,185)	0,001	(0,108)	0,005	(0,483)
R_{t-1}			-0,026	(-8,674)***			-0,028	(-9,440)***
R_{world}			-0,063	(-14,390)***			-0,056	(-12,885)***
ΔEPU			0,107	(4,958)***			0,014	(0,674)
ΔVIX			0,001	(0,025)			0,018	(0,547)
Vol_{t-1}			0,427	(32,340)***			0,155	(10,481)***
Factors	Country, Month		Country, Month		Country, YearMonth		Country, YearMonth	
Adj. R^2	0,774		0,835		0,848		0,857	
Obs	9094		9087		9094		9087	
df	9044		9032		8996		8984	

When adding the remaining control variables, the results remain mostly unaltered, save for a decrease in SWAV's statistically significance in explaining volatility. Another meaningful result is EPU's sensitivity to the use of different time factors, which is unlike our previous analyses where it remained reliably consistent with our expectations.

These findings, while closer to expected than in the previous sections, still highlight issues with using SWAV as a proxy for investor sentiment. Depending on which model specification is utilized, results change from consistent with the literature and statistically significant, to insignificant, to completely contrary to the theory while statistically significant.

6. Conclusion

6.1. Main results and their context within the literature

The results presented in this study lead to the conclusion that music sentiment, at least as it is calculated here, is not a good predictor of stock returns. It is often inconsistent, changing considerably in statistical significance and even direction when predicting stock market returns based on what model specification and control variables are being used. As such, our findings conflict with the ones presented in the literature (Fernandez-Perez et al., 2020; Edmans et al., 2021).

We expected weekly changes in music sentiment to be positively correlated with same-week returns in the stock market, as a consequence of positive mood influencing investors' trading decisions, while being negatively correlated with next week returns, after the readjustment of expectations and the actions of sophisticated traders reverted prices back to their fundamental values. We also expected smaller stock to be more susceptible to investor sentiment than larger stock, as a result of being harder to evaluate and less popular among arbitrageurs. Finally, we anticipated larger shocks to sentiment to be associated with higher volatility in the stock market, and for that effect to be stronger when those shocks were negative.

The methods employed to test these hypotheses appear to reject them. Not only does SWAV often behave differently to what the general theory on investor sentiment predicts, they are contrary to the work already done on this specific topic, namely in Edmans et al. (2021). When using country and month as the fixed factors, contemporaneous and lagged music sentiment both move in opposite directions in both analyses. It is important to highlight some methodological differences between the studies: this research does not include deseasonalized cloud coverage (a weather-based control variable), and the selection of countries differs to some extent as well. Another change is the usage of weekly charts provided by Spotify, rather than the construction of weekly charts based on daily ones, which leads to a difference in the weekday in which a week ends (from Friday, in Edmans et al., 2021, to Thursday, which is the day for which Spotify's weekly charts are made available). While using daily data to compute weekly charts allows for the flexibility of choosing the end-of-week day, it runs the risk of missing songs that, while not belonging on the charts based on available daily data, they could be based on weekly data (any song not featuring on the daily top-200 would be assumed to have zero plays on that day). Finally, the time period is also altered, with this study adding the year of 2021 to the analysis, although such an inclusion does not appear to be responsible for the different results (see table 15).

However, should these deviations result in such contradictory findings if music sentiment was an appropriate and consistent predictor of stock market investment? Particularly when other variables, for example the returns on the MSCI Total Return Index and Economic Policy Uncertainty, behave not just similarly across both studies, but in conformity with the how they would be expected to based on the theory?

The expectations on the differences between smaller and larger stock were also challenged. What divergences there were in the explanatory power of SWAV when using small stock and large stock return as the dependent variables opposed our preconceptions. Music sentiment was more significant in explaining large stock market returns presented than smaller stock returns, which goes against the notions of characteristics of the financial assets more likely to see their price fluctuate with noise and mood.

Lastly, the findings regarding the impact of music sentiment on volatility were, despite closer to conformant, also inconsistent. SWAV showed once again a significant sensitivity to changes to the model specifications, while no evidence of volatility reacting differently to negative and positive variations in sentiment was found.

In light of these discoveries, music sentiment as computed using the stream-weighted average of Spotify's valence for chart-topping songs cannot be concluded to be a suitable proxy of investor sentiment, and therefore, an effective predictor of stock market returns.

6.2. Limitations and further research

The conclusions in this study come with some caveats caused by its limitations.

One is how the control variables are only available for the United States. EPU is only available at the required frequency for the United States, while VIX and ADS are US-exclusive measures altogether. Perhaps the results would be different measures of economic uncertainty, market volatility and macroeconomic context were employed for each individual country. Even in the case of the small cap and large cap MSCI Index, some countries have unavailable data for certain time periods, leading to fewer observations[11].

Another limitation has to do with the use of weekly data. On the one hand, weekly data is not as high frequency as daily data would be, and could not, therefore, capture changes in sentiment as immediately; on the other, it may be more sensitive specific events – such as holidays – than with a larger timeframe. One event that strongly influences music sentiment is the release of new tracks by popular artists. New releases often get a meaningful number of streams, influencing SWAV. While we theorize music can influence mood, it might be that the effect is not strong enough, and there is currently no way identify and isolate this effect with the methodology employed. The removal of the top 50 songs, such as in Edmans et al. (2021) thus runs into two problems: one is it does not necessarily remove all new tracks, as some are scattered among the remaining 150 ones; the other is that it excludes from the analysis the most important songs, as they are the ones people are listening to the most. One alternative would be conduct a study which excluded songs released in the few weeks before the chart. However, new tracks by popular artists tend to have enough staying power to remain in the charts for several weeks, and would thus remain unaffected by such approach for long.

Finally, there is the issue regarding at what time Spotify makes their charts available. While it doesn't present an issue in terms of a purely historical analysis such as this one, any forward-looking approach, or even the integration of music sentiment in investment decisions, would have to take this into account.

Besides attempting to deal with the presented issues, there are a few approaches future research on the topic could take. One would be calculating music sentiment differently to how SWAV computed, by using another formula or music characteristic other than valence. Another hypothesis could be using the consumption of different media altogether. On the side of the dependent variable, using different financial market indices, or even asset classes altogether, is an avenue worth exploring.

[11] For the large cap index, between not available data and instances of the index not changing from one week to the next (sometimes for several weeks on end), Argentina is missing 29 weeks, Austria 77 weeks, Indonesia 1 week, New Zealand 184 weeks, and Turkey 29 weeks. In the case of the small cap index, Czech Republic is missing 6 weeks, and Indonesia 1 week. For the main index (all cap), Indonesia is also missing 1 week, as is Portugal

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Appendices

Table 8: Information regarding songs recording the lowest and highest valence, as well as those registering the most streams and most weeks on the charts, featuring in at least one top 200 chart, by country, for the period between 2016/12/29 and 2021/12/30. In case two songs are tied for a category, the song with the most plays was selected.

Country	Lowest valence song		Highest valence song		Most streamed song		Most chart features	
Argentina	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	El Dipy – Dame Tu Mano	0,979	Maluma – Hawái	83 661 977	Gustavo Cerati – Crimen	262
Australia	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Earth, Wind & Fire - September	0,982	Ed Sheeran – Shape of You	114 955 141	James Arthur – Say You Won't Let Go	262
Austria	Claudius Vlasak – The Arrival	0,031	Gene Austry – Here Comes Santa Claus	0,976	Tones And I – Dance Monkey	13 412 269	Bonez MC, RAF Camora, Maxwell - Ohne Mein Team	260
Belgium	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Earth, Wind & Fire - September	0,982	Tones And I – Dance Monkey	26 073 962	Ed Sheeran – Shape of You	243
Brazil	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Os Barões da Pisadinha – Já Que Me Ensinou a Beber	0,975	Israel & Rodolfo – Batom de Cereja	192 632 143	Imagine Dragons – Believer	202
Canada	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Earth, Wind & Fire - September	0,982	Lewis Capaldi – Someone You Loved	83 123 608	James Arthur – Say You Won't Let Go	248
Chile	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Hermanos Morales – Tus Ojos Morenos Vide	0,980	Jhay Cortez, J Balvin, Bad Bunny – No Me Conoce - Remix	90 731 648	Danny Ocean – Me Rehúso	247
Colombia	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Guillermo Buitrago, Los Trovadores de Baru – Vispera de Año Nuevo	0,989	Maluma – Hawái	34 265 660	Danny Ocean – Me Rehúso	262
Czech Republic	Samey – v korunach stromov	0,011	Earth, Wind & Fire - September	0,982	Viktor Sheen, Nik Tendo, Calin, Hasan – Až na měsíc	12 661 562	Imagine Dragons – Believer	255
Denmark	Herrelandsholdet – Der er et yndigt land - Live	0,022	Earth, Wind & Fire - September	0,982	Ed Sheeran – Shape of You	32 484 838	James Arthur – Say You Won't Let Go	217
Finland	David Guetta, MORTEN, Sia – Titanium	0,031	Leevi and the leavings – Pohjois-Karjala	0,978	Ed Sheeran – Shape of You	20 601 071	Poju – Esson baariin	224
France	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Earth, Wind & Fire - September	0,982	Ninho – La vie qu'on mène	109 806 580	Lomepal – Trop beau	158
Germany	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Gene Austry – Here Comes Santa Claus	0,976	Apache 207 – Roller	192 297 593	Bonez MC, RAF Camora, Maxwell - Ohne Mein Team	235
Greece	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Gene Austry – Here Comes Santa Claus	0,976	Mente Fuerte, Hawk, Baghdad – Caliente	9 627 300	Travis Scott – goosebumps	225
Hong Kong	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Justin Bieber, Lil Dicky – Running Over	0,977	Ed Sheeran – Shape of You	11 732 672	Jason Chan – 你瞞我瞞	262
Hungary	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Earth, Wind & Fire - September	0,982	Tones And I – Dance Monkey	8 473 801	Punnany Massif – Élvezd	257
Indonesia	Justin Hurwitz – Planetarium	0,040	Shawn Mendes – There's Nothing Holdin' Me Back	0,969	Pamungkas – To the Bone	110 422 662	Payung Teduh – Untuk Perempuan Yang Sedang Di Pelukan	262
Ireland	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Earth, Wind & Fire - September	0,982	Tones And I – Dance Monkey	21 634 450	The Killers – Mr. Brighside	262
Italy	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Goodboys – Bongo Cha Cha Cha	0,973	Salmo, NSTASIA – IL CIELO NELLA STANZA	123 387 122	Izi – Chic	188
Malaysia	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Justin Bieber, Lil Dicky – Running Over	0,977	Lewis Capaldi – Someone You Loved	16 610 400	James Arthur – Say You Won't Let Go	262
Mexico	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Aldo Trujillo – Todos Hablan, Nada Saben	0,976	J Balvin, Bad Bunny – LA CANCIÓN	258 048 947	Luis Miguel – Ahora Te Puedes Marchar	262
Netherlands	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Noord-Hollands Kinderkoor – Hop, Hop, Hop, Paardje In Galop	0,989	Davina Michelle – Duurt Te Lang	91 257 254	De Jeugd Van Tegenwoordig – Sterrenstof	217
New Zealand	TOOL – Legion Inoculant	0,026	Earth, Wind & Fire - September	0,982	Ed Sheeran – Shape of You	25 375 999	The Killers – Mr. Brighside	261
Norway	David Guetta, MORTEN, Sia – Titanium	0,031	Justin Bieber, Lil Dicky – Running Over	0,977	Tones And I – Dance Monkey	49 312 191	Stavangerkameratene – Bare så du vett det	235
Philippines	Joji – Ew	0,038	José Feliciano – Feliz Navidad	0,967	Ben&Ben – Kathang Isip	155 387 216	James Arthur – Say You Won't Let Go	262
Poland	Pezet – Droga (prod. Auer)	0,027	Shawn Mendes – There's Nothing Holdin' Me Back	0,969	White 2115 – California	41 942 136	White 2115 – California	184
Portugal	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Capitão Fausto – Boa Memória	0,976	Wet Bed Gang – Devias Ir	15 231 147	Travis Scott – goosebumps	226
Singapore	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Shawn Mendes – There's Nothing Holdin' Me Back	0,969	Ed Sheeran – Shape of You	29 039 218	James Arthur – Say You Won't Let Go	262
Spain	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Nil Moliner – Mi Religión	0,973	KAROL G, Nicki Minaj – Tusa	116 333 005	Pereza – Princesas	194
Sweden	David Guetta, MORTEN, Sia – Titanium	0,031	Earth, Wind & Fire - September	0,982	Ed Sheeran – Shape of You	81 907 479	Journey – Don't Stop Believin'	220
Switzerland	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Earth, Wind & Fire - September	0,982	Tones And I – Dance Monkey	21 048 030	Imagine Dragons – Believer	214
Taiwan	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Eason Chan – 放	0,967	831 - 想見你想見你想見你(電視劇"想見你"片尾曲)	24 860 286	Eric Chou – 你, 好不好? - TVBS連續劇【遺憾拼圖】片尾曲	262
Turkey	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Boney M. – Rasputin	0,972	Yüzyüzeyken Konuşuruz – Dinle Beni Bi'	73 150 904	mor ve ötesi – Bir Derdim Var	257
United Kingdom	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Earth, Wind & Fire - September	0,982	Ed Sheeran – Shape of You	210 129 331	The Killers – Mr. Brighside	262
United States	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Earth, Wind & Fire - September	0,982	Travis Scott – goosebumps	633 896 377	Travis Scott – goosebumps	257
World	Billie Eilish, ROSALÍA – Los Vas a Olvidar	0,032	Earth, Wind & Fire - September	0,982	Ed Sheeran – Shape of You	2 977 817 131	Ed Sheeran – Shape of You	257

Figure 5: Weekly SWAV, by country from 2016/12/29 to 2021/12/30

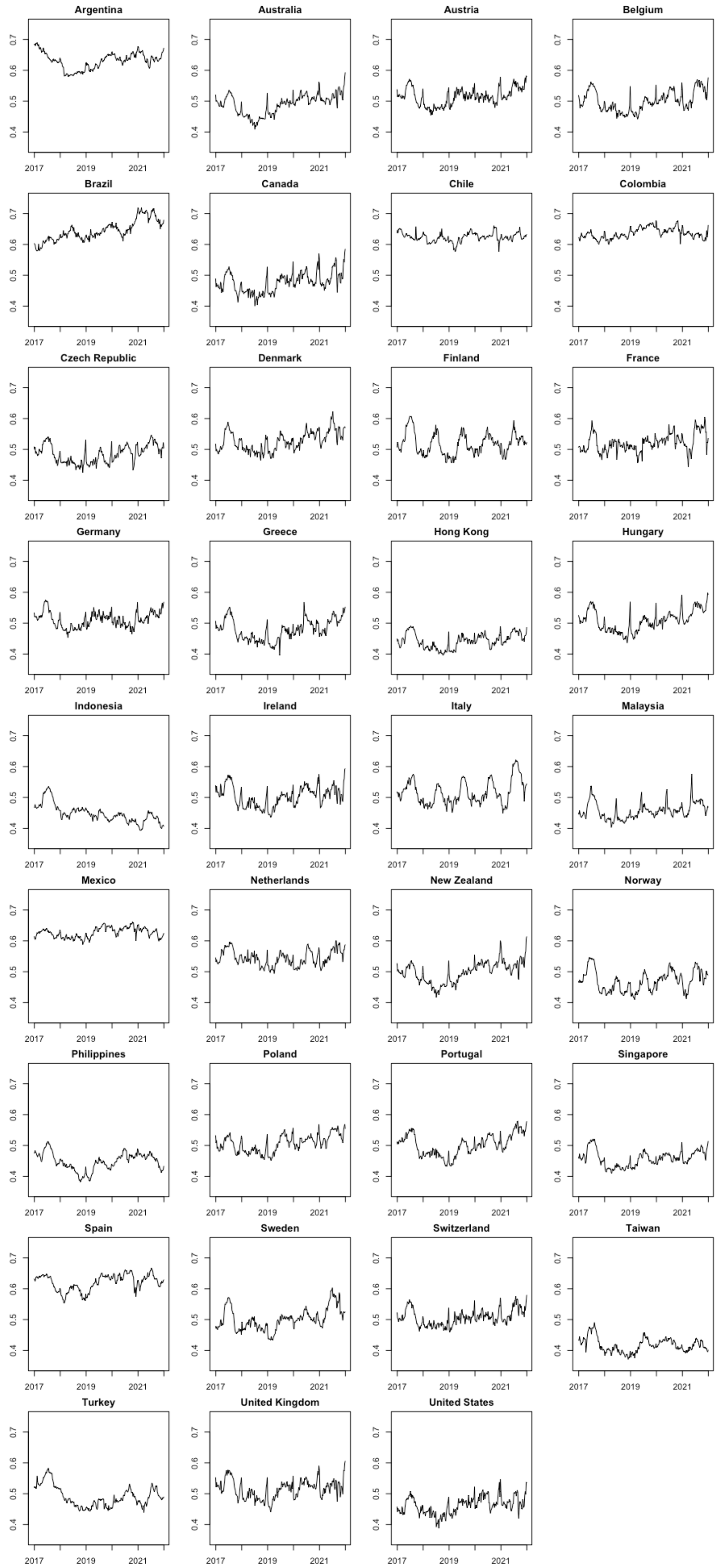

Figure 6: Weekly music sentiment (ΔSWAV), by country, from 2017/01/05 to 2021/12/30

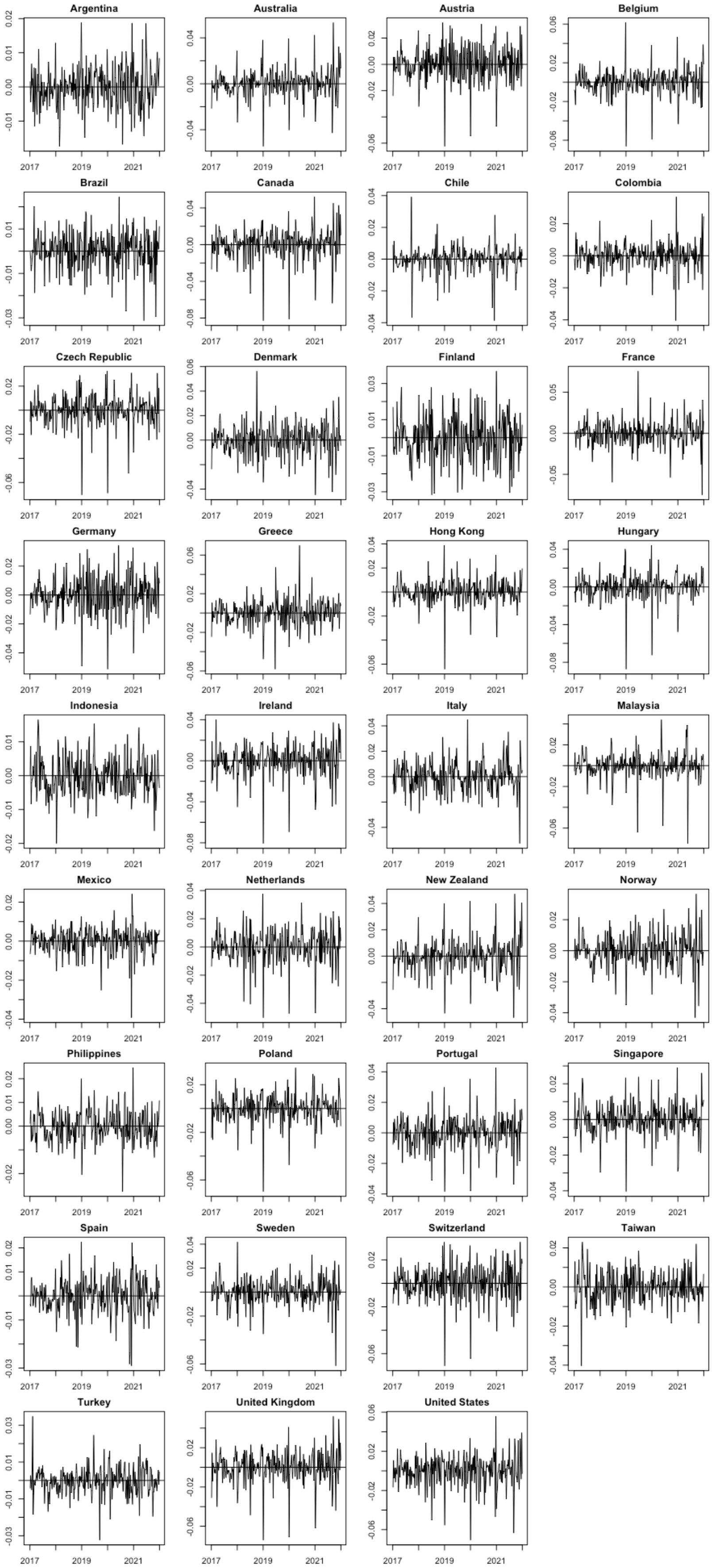

Table 9: Weekly music sentiment (ΔSWAV) descriptive statistics (in %)

Country	Mean	SD	Min	Q1	Median	Q3	Max	Obs
Argentina	-0,0041	0,5858	-1,7358	-0,4004	0,0234	0,0234	1,8787	261
Australia	0,0277	1,1776	-5,4370	-0,4506	0,0392	0,0392	5,3157	261
Austria	0,0155	1,2799	-6,2315	-0,7513	-0,0068	-0,0068	3,1667	261
Belgium	0,0221	1,2958	-6,6217	-0,5584	0,1081	0,1081	6,1421	261
Brazil	0,0297	0,8195	-3,1194	-0,3685	0,0416	0,0416	2,4405	261
Canada	0,0367	1,6452	-8,2647	-0,6279	0,2135	0,2135	5,1875	261
Chile	-0,0015	0,7762	-3,8623	-0,2863	0,0813	0,0813	3,9117	261
Colombia	0,0152	0,7896	-4,0407	-0,3515	0,0448	0,0448	3,6659	261
Czech Republic	-0,0021	1,2620	-7,0220	-0,4932	0,0116	0,0116	3,2331	261
Denmark	0,0195	1,2609	-4,4586	-0,6621	0,0960	0,0960	5,6146	261
Finland	0,0066	1,1966	-3,1642	-0,6737	0,0542	0,0542	3,6773	261
France	0,0115	1,5400	-7,4915	-0,6943	0,0552	0,0552	7,5410	261
Germany	0,0133	1,2422	-5,1223	-0,7031	0,0844	0,0844	3,4195	261
Greece	0,0174	1,3082	-5,7986	-0,6548	0,0355	0,0355	6,9867	261
Hong Kong	0,0142	0,9964	-6,4069	-0,4480	-0,0240	-0,0240	3,8630	261
Hungary	0,0254	1,3086	-8,7188	-0,4932	0,0825	0,0825	4,3925	261
Indonesia	-0,0241	0,5616	-1,9974	-0,4055	-0,0746	-0,0746	1,6489	261
Ireland	0,0207	1,5244	-8,0477	-0,6243	0,1017	0,1017	3,9900	261
Italy	0,0099	1,1579	-5,2568	-0,6088	-0,0071	-0,0071	4,4778	261
Malaysia	0,0067	1,2189	-7,4583	-0,4626	-0,0066	-0,0066	4,3968	261
Mexico	0,0040	0,6622	-3,9204	-0,3429	0,1013	0,1013	2,4122	261
Netherlands	0,0161	1,1783	-5,0111	-0,5675	0,0585	0,0585	3,7517	261
New Zealand	0,0333	1,2061	-4,6728	-0,4609	0,0498	0,0498	4,7125	261
Norway	0,0075	1,0400	-4,3090	-0,5209	0,0225	0,0225	3,6477	261
Philippines	-0,0162	0,6319	-2,7517	-0,4188	-0,0390	-0,0390	2,4556	261
Poland	0,0080	1,1518	-6,9649	-0,5421	0,0496	0,0496	3,4114	261
Portugal	0,0253	1,0314	-3,8311	-0,4732	0,0900	0,0900	4,2532	261
Singapore	0,0195	0,8692	-4,0339	-0,4156	0,0166	0,0166	2,8908	261
Spain	-0,0011	0,7264	-2,9005	-0,4136	0,0163	0,0163	2,2345	261
Sweden	0,0177	1,1053	-6,1437	-0,5594	0,0367	0,0367	4,1642	261
Switzerland	0,0217	1,4268	-7,0215	-0,8288	0,0421	0,0421	3,5086	261
Taiwan	-0,0127	0,7950	-4,0269	-0,4486	-0,0493	-0,0493	2,2897	261
Turkey	-0,0127	0,7245	-3,2277	-0,3777	-0,0256	-0,0256	3,4740	261
United Kingdom	0,0204	1,5876	-7,3932	-0,7037	0,0601	0,0601	5,1828	261
United States	0,0293	1,5694	-7,0537	-0,6455	0,1757	0,1757	5,5610	261
Full Sample	0,0120	1,1431	-8,7188	-0,5035	0,0357	0,5788	7,5410	9135

Figure 7: Index chart of weekly MSCI Total Return Index, by country, from 2016/12/22 to 2021/12/30

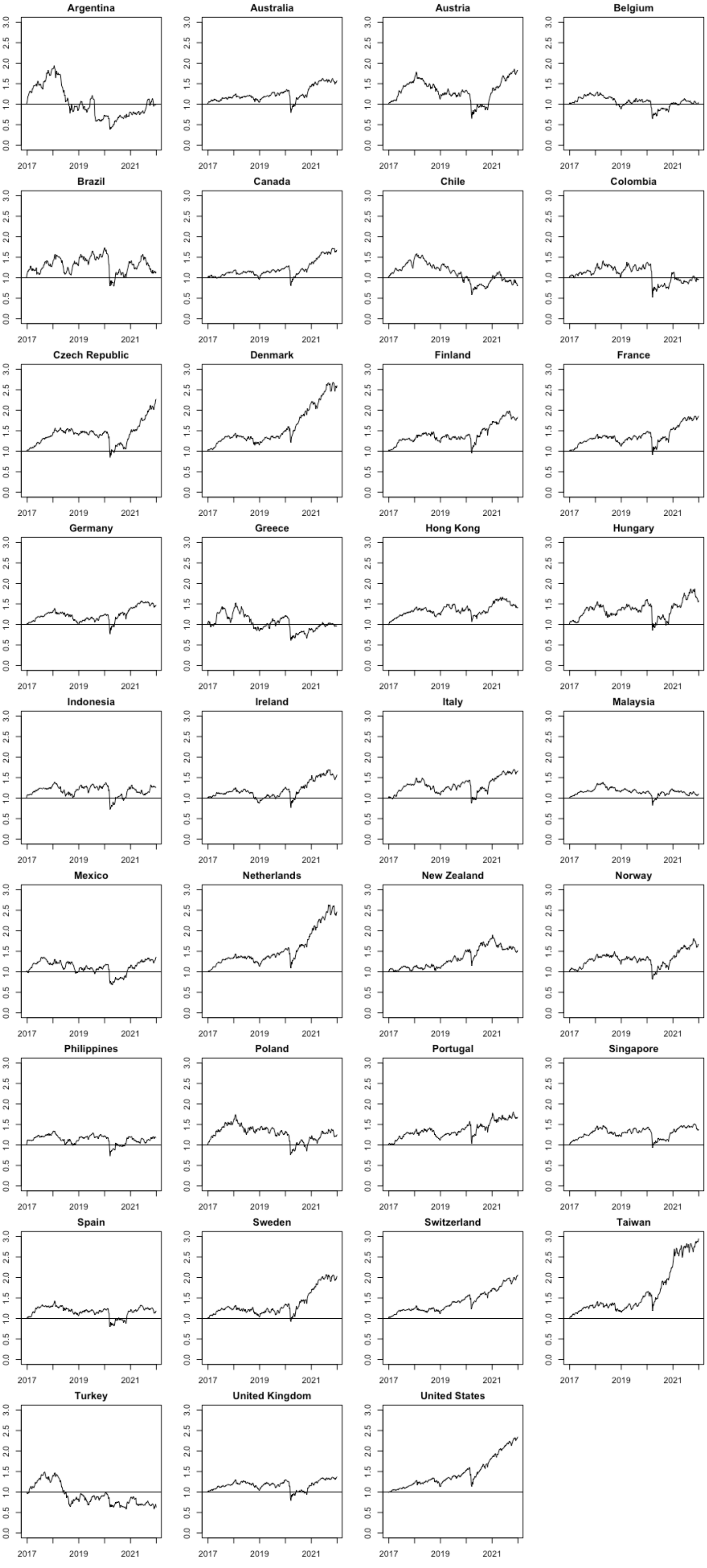

Figure 8: Weekly MSCI Total Return Index log returns, by country, from 2016/12/29 to 2021/12/30 (in %)

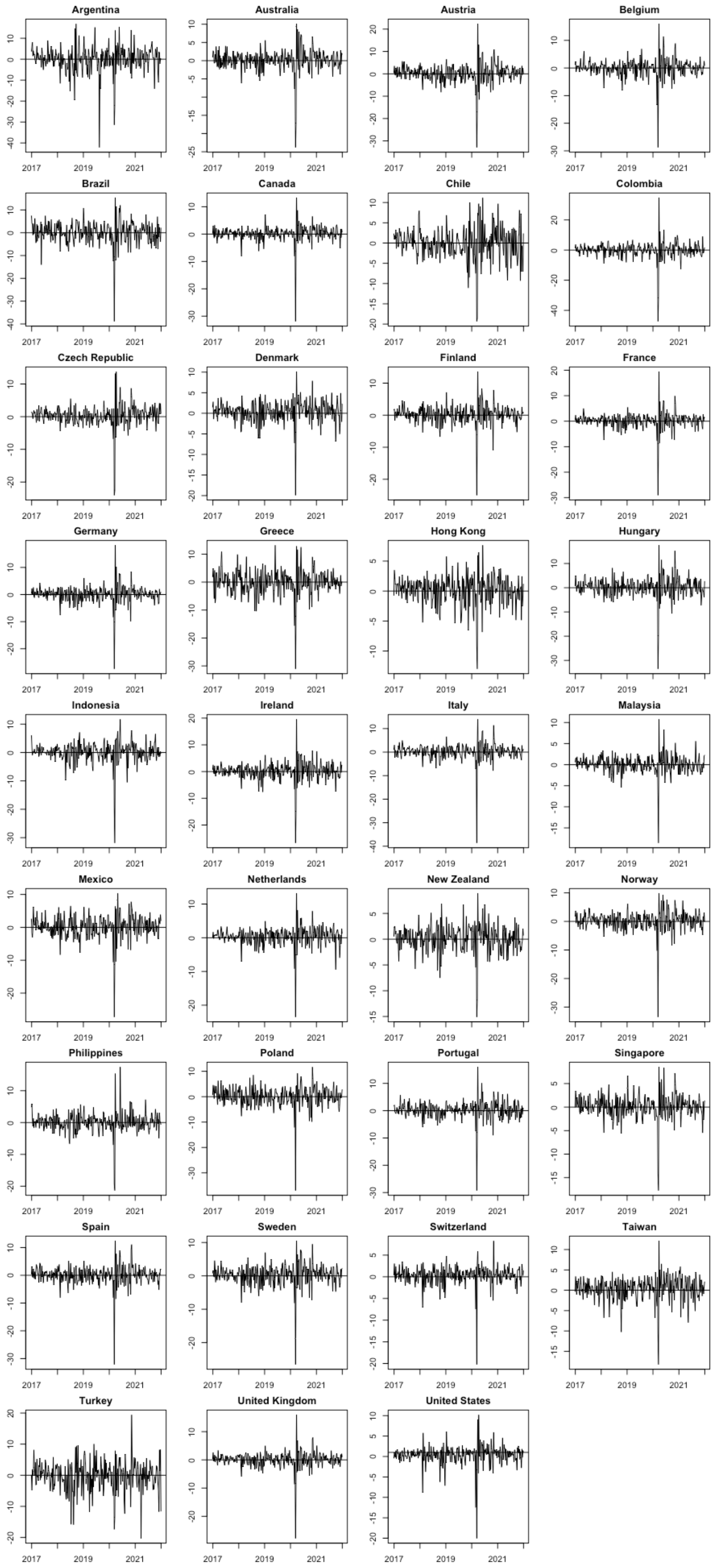

Table 10: Weekly MSCI Total Return Index log returns descriptive statistics (in %)

Country	Mean	SD	Min	Q1	Median	Q3	Max	Obs
Argentina	-0,0041	6,2380	-42,0521	-2,6190	0,3977	3,2482	16,7939	262
Austria	0,2298	4,2903	-32,8503	-1,4698	0,2728	2,2843	22,2715	262
Australia	0,1736	2,9729	-23,7682	-0,9604	0,4199	1,5024	10,0578	262
Belgium	0,0147	3,4274	-28,7069	-1,0824	0,2415	1,3395	15,9290	262
Brazil	0,0486	4,8459	-38,7824	-2,1754	0,2037	2,9590	15,2550	262
Canada	0,1962	2,9867	-31,8437	-0,8098	0,3043	1,4459	13,2158	262
Switzerland	0,2770	2,2240	-20,1854	-0,4419	0,3925	1,3769	8,2422	262
Chile	-0,0769	3,8886	-19,2876	-2,2013	0,0860	2,1438	11,1314	262
Colombia	-0,0113	5,5080	-47,1799	-1,7120	0,2101	2,3273	34,5743	262
Czech Republic	0,3130	3,2623	-24,0063	-1,0987	0,5239	1,7438	13,7045	262
Germany	0,1463	3,2589	-27,3672	-0,9765	0,2850	1,5837	18,1407	262
Denmark	0,3654	2,6560	-19,8865	-0,9393	0,5900	1,7431	10,0609	262
Spain	0,0656	3,4289	-32,0633	-1,3385	0,1789	1,7378	12,3240	262
Finland	0,2306	3,0312	-24,9488	-1,1449	0,4188	1,5837	13,5155	262
France	0,2368	3,2863	-29,0091	-0,8717	0,5556	1,5875	19,3495	262
United Kingdom	0,1207	2,9220	-27,7672	-1,0001	0,3789	1,4329	15,8975	262
Greece	-0,0147	4,5469	-30,9974	-2,1218	0,0276	2,4850	13,1345	262
Hong Kong	0,1326	2,4157	-12,9547	-0,9768	0,4028	1,6239	7,6196	262
Hungary	0,1751	4,2711	-33,4415	-1,9223	0,2630	2,1902	17,4857	262
Indonesia	0,0891	3,7065	-31,8190	-1,1976	0,4015	1,8409	11,6559	261
Ireland	0,1724	3,4777	-26,6543	-1,3655	0,3654	1,8720	19,5016	262
Italy	0,1953	3,6073	-38,5556	-1,1843	0,4358	1,8377	13,8907	262
Mexico	0,1174	3,5472	-27,2326	-1,6247	0,1200	2,1477	10,2855	262
Malaysia	0,0395	2,2022	-18,5368	-0,9777	0,1131	0,9987	10,7225	262
Netherlands	0,3444	2,8419	-23,4784	-0,7319	0,4668	1,7311	13,1220	262
Norway	0,1950	3,4850	-33,4313	-1,3647	0,4815	2,0028	9,7624	262
New Zealand	0,1592	2,6241	-15,0757	-1,0779	0,2864	1,6489	8,8565	262
Philippines	0,0632	3,2589	-21,3066	-1,3855	0,0541	1,3703	17,3997	262
Poland	0,0867	4,0768	-36,9118	-2,0176	0,1952	2,4554	11,6444	262
Portugal	0,1980	3,3166	-29,2136	-1,0847	0,3859	1,7344	15,9645	261
Sweden	0,2711	3,2205	-26,5073	-1,2380	0,6141	1,9374	10,4230	262
Singapore	0,1234	2,5523	-17,7116	-1,1218	0,1505	1,3961	8,4989	262
Turkey	-0,1794	4,8687	-20,2420	-2,7714	0,3377	2,6487	19,3741	262
Taiwan	0,4131	2,9376	-18,1895	-0,8002	0,7046	2,2831	12,0869	262
United States	0,3257	2,4804	-20,0041	-0,4878	0,5095	1,4499	10,1584	262
World	0,1495	3,5856	-47,1799	-1,2642	0,3444	1,7933	34,5743	9168

Table 11: Descriptive statistics for the control variables. World Returns is the weekly MSCI Total Return Index log returns for the world market (in %), ΔEPU is the weekly relative change in the Economic Policy Uncertainty, ΔVIX is the weekly relative change in the CBOE Volatility Index, and ΔADS is the weekly nominal change in the Aruoba-Diebold-Scotti Business Conditions Index.

Variable	Mean	SD	Min	Q1	Median	Q3	Max
World Returns	0,2766	2,3849	-20,9893	-0,5447	0,4255	1,4214	10,1924
ΔEPU	0,0388	0,2946	-0,4893	-0,1485	-0,0139	0,1768	1,9750
ΔVIX	0,0177	0,2106	-0,4283	-0,0943	-0,0142	0,0725	1,5167
ΔADS	-0,0023	1,1526	-7,3948	-0,1131	-0,0216	0,0824	8,2084

Figure 9: Weekly volatility of the daily MSCI Total Return Index log returns, from 2016/12/29 to 2021/12/30

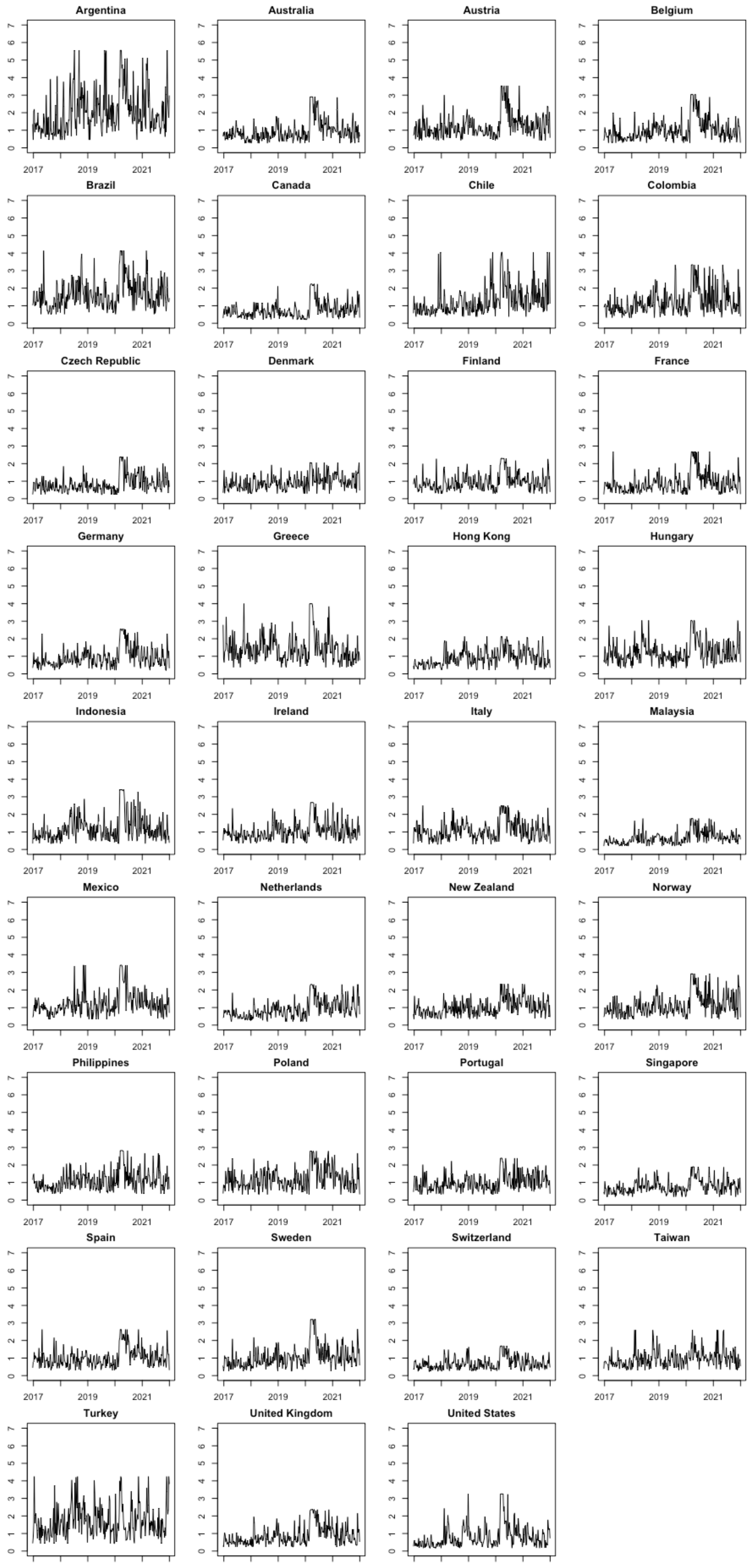

Table 12: Country weekly SWAV Pearson correlation matrix

	Argentina	Austria	Australia	Belgium	Brazil	Canada	Switzerland	Chile	Colombia	Czech Republic	Germany	Denmark	Spain	Finland	France	United Kingdom	Greece	Hong Kong
Argentina	1,000	0,509	0,693	0,486	0,114	0,495	0,456	0,597	0,255	0,466	0,472	0,362	0,574	0,100	0,131	0,519	0,516	0,475
Austria	0,509	1,000	0,770	0,708	0,273	0,817	0,908	0,156	0,179	0,747	0,940	0,725	0,508	0,424	0,428	0,713	0,689	0,780
Australia	0,693	0,770	1,000	0,802	0,373	0,897	0,794	0,347	0,272	0,736	0,627	0,756	0,603	0,353	0,519	0,799	0,790	0,789
Belgium	0,486	0,708	0,802	1,000	0,268	0,796	0,848	0,342	0,077	0,854	0,581	0,790	0,624	0,620	0,757	0,765	0,860	0,800
Brazil	0,114	0,273	0,373	0,268	1,000	0,380	0,306	0,027	0,214	0,253	0,113	0,418	0,228	0,011	0,318	0,137	0,216	0,272
Canada	0,495	0,817	0,897	0,796	0,380	1,000	0,861	0,228	0,287	0,742	0,685	0,802	0,521	0,436	0,557	0,840	0,778	0,788
Switzerland	0,456	0,908	0,794	0,848	0,306	0,861	1,000	0,205	0,152	0,796	0,830	0,756	0,573	0,546	0,610	0,780	0,749	0,823
Chile	0,597	0,156	0,347	0,342	0,027	0,228	0,205	1,000	0,299	0,206	0,107	0,207	0,510	0,128	0,204	0,296	0,355	0,207
Colombia	0,255	0,179	0,272	0,077	0,214	0,287	0,152	0,299	1,000	-0,058	0,142	0,170	0,461	0,025	0,052	0,203	-0,003	0,089
Czech Republic	0,466	0,747	0,736	0,854	0,253	0,742	0,796	0,206	-0,058	1,000	0,635	0,792	0,583	0,577	0,527	0,751	0,839	0,785
Germany	0,472	0,940	0,627	0,581	0,113	0,685	0,830	0,107	0,142	0,635	1,000	0,563	0,409	0,379	0,293	0,639	0,565	0,695
Denmark	0,362	0,725	0,756	0,790	0,418	0,802	0,756	0,207	0,170	0,792	0,563	1,000	0,542	0,584	0,566	0,757	0,788	0,762
Spain	0,574	0,508	0,603	0,624	0,228	0,521	0,573	0,510	0,461	0,583	0,409	0,542	1,000	0,545	0,393	0,570	0,576	0,577
Finland	0,100	0,424	0,353	0,620	0,011	0,436	0,546	0,128	0,025	0,577	0,379	0,584	0,545	1,000	0,542	0,582	0,605	0,590
France	0,131	0,428	0,519	0,757	0,318	0,557	0,610	0,204	0,052	0,527	0,293	0,566	0,393	0,542	1,000	0,444	0,609	0,473
United Kingdom	0,519	0,713	0,799	0,765	0,137	0,840	0,780	0,296	0,203	0,751	0,639	0,757	0,570	0,582	0,444	1,000	0,791	0,766
Greece	0,516	0,689	0,790	0,860	0,216	0,778	0,749	0,355	-0,003	0,839	0,565	0,788	0,576	0,605	0,609	0,791	1,000	0,757
Hong Kong	0,475	0,780	0,789	0,800	0,272	0,788	0,823	0,207	0,089	0,785	0,695	0,762	0,577	0,590	0,473	0,766	0,757	1,000
Hungary	0,556	0,839	0,861	0,910	0,345	0,863	0,882	0,283	0,095	0,901	0,713	0,855	0,600	0,580	0,583	0,834	0,874	0,857
Indonesia	-0,043	0,093	-0,100	0,139	-0,627	-0,066	0,133	0,017	-0,301	0,221	0,233	0,024	0,034	0,436	-0,003	0,187	0,174	0,268
Ireland	0,541	0,722	0,810	0,816	0,157	0,833	0,803	0,305	0,145	0,833	0,625	0,788	0,625	0,628	0,480	0,969	0,847	0,792
Italy	0,137	0,537	0,426	0,720	0,187	0,494	0,632	0,262	0,038	0,656	0,428	0,642	0,573	0,700	0,642	0,478	0,608	0,543
Mexico	0,515	0,322	0,514	0,361	0,298	0,444	0,343	0,449	0,771	0,294	0,240	0,418	0,696	0,239	0,155	0,458	0,306	0,378
Malaysia	0,288	0,679	0,635	0,651	0,248	0,629	0,689	0,110	0,104	0,684	0,603	0,699	0,511	0,604	0,422	0,602	0,676	0,808
Netherlands	0,185	0,532	0,466	0,772	0,089	0,554	0,648	0,194	-0,089	0,709	0,478	0,681	0,409	0,719	0,530	0,684	0,671	0,610
Norway	0,339	0,646	0,618	0,829	0,062	0,692	0,749	0,231	0,044	0,818	0,542	0,755	0,644	0,818	0,629	0,738	0,805	0,737
New Zealand	0,709	0,692	0,961	0,716	0,437	0,857	0,718	0,332	0,272	0,643	0,545	0,687	0,503	0,228	0,464	0,740	0,716	0,705
Philippines	0,573	0,469	0,621	0,636	0,109	0,528	0,546	0,281	0,009	0,713	0,382	0,616	0,585	0,579	0,318	0,682	0,656	0,717
Poland	0,473	0,766	0,773	0,795	0,496	0,814	0,786	0,366	0,294	0,767	0,626	0,810	0,637	0,505	0,570	0,754	0,744	0,740
Portugal	0,516	0,719	0,790	0,899	0,325	0,755	0,819	0,345	0,024	0,849	0,587	0,774	0,710	0,671	0,617	0,752	0,848	0,791
Sweden	0,246	0,647	0,632	0,791	0,447	0,689	0,750	0,251	0,037	0,770	0,504	0,822	0,603	0,716	0,632	0,662	0,785	0,767
Singapore	0,506	0,814	0,793	0,804	0,113	0,770	0,829	0,228	0,090	0,800	0,751	0,751	0,592	0,660	0,487	0,790	0,781	0,910
Turkey	0,417	0,359	0,350	0,596	-0,293	0,281	0,437	0,298	-0,284	0,596	0,361	0,422	0,365	0,584	0,325	0,503	0,586	0,526
Taiwan	0,389	0,503	0,526	0,663	-0,164	0,511	0,590	0,251	0,072	0,635	0,490	0,508	0,629	0,731	0,421	0,636	0,616	0,742
United States	0,469	0,720	0,857	0,673	0,361	0,937	0,764	0,140	0,321	0,634	0,598	0,728	0,468	0,344	0,428	0,787	0,674	0,762
World	0,625	0,796	0,908	0,838	0,359	0,912	0,855	0,337	0,298	0,798	0,677	0,849	0,642	0,533	0,530	0,874	0,806	0,866

(continuation)

	Hungary	Indonesia	Ireland	Italy	Mexico	Malaysia	Netherlands	Norway	New Zealand	Philippines	Poland	Portugal	Sweden	Singapore	Turkey	Taiwan	United States	World
Argentina	0,556	-0,043	0,541	0,137	0,515	0,288	0,185	0,339	0,709	0,573	0,473	0,516	0,246	0,506	0,417	0,389	0,469	0,625
Austria	0,839	0,093	0,722	0,537	0,322	0,679	0,532	0,646	0,692	0,469	0,766	0,719	0,647	0,814	0,359	0,503	0,720	0,796
Australia	0,861	-0,100	0,810	0,426	0,514	0,635	0,466	0,618	0,961	0,621	0,773	0,790	0,632	0,793	0,350	0,526	0,857	0,908
Belgium	0,910	0,139	0,816	0,720	0,361	0,651	0,772	0,829	0,716	0,636	0,795	0,899	0,791	0,804	0,596	0,663	0,673	0,838
Brazil	0,345	-0,627	0,157	0,187	0,298	0,248	0,089	0,062	0,437	0,109	0,496	0,325	0,447	0,113	-0,293	-0,164	0,361	0,359
Canada	0,863	-0,066	0,833	0,494	0,444	0,629	0,554	0,692	0,857	0,528	0,814	0,755	0,689	0,770	0,281	0,511	0,937	0,912
Switzerland	0,882	0,133	0,803	0,632	0,343	0,689	0,648	0,749	0,718	0,546	0,786	0,819	0,750	0,829	0,437	0,590	0,764	0,855
Chile	0,283	0,017	0,305	0,262	0,449	0,110	0,194	0,231	0,332	0,281	0,366	0,345	0,251	0,228	0,298	0,251	0,140	0,337
Colombia	0,095	-0,301	0,145	0,038	0,771	0,104	-0,089	0,044	0,272	0,009	0,294	0,024	0,037	0,090	-0,284	0,072	0,321	0,298
Czech Republic	0,901	0,221	0,833	0,656	0,294	0,684	0,709	0,818	0,643	0,713	0,767	0,849	0,770	0,800	0,596	0,635	0,634	0,798
Germany	0,713	0,233	0,625	0,428	0,240	0,603	0,478	0,542	0,545	0,382	0,626	0,587	0,504	0,751	0,361	0,490	0,598	0,677
Denmark	0,855	0,024	0,788	0,642	0,418	0,699	0,681	0,755	0,687	0,616	0,810	0,774	0,822	0,751	0,422	0,508	0,728	0,849
Spain	0,600	0,034	0,625	0,573	0,696	0,511	0,409	0,644	0,503	0,585	0,637	0,710	0,603	0,592	0,365	0,629	0,468	0,642
Finland	0,580	0,436	0,628	0,700	0,239	0,604	0,719	0,818	0,228	0,579	0,505	0,671	0,716	0,660	0,584	0,731	0,344	0,533
France	0,583	-0,003	0,480	0,642	0,155	0,422	0,530	0,629	0,464	0,318	0,570	0,617	0,632	0,487	0,325	0,421	0,428	0,530
United Kingdom	0,834	0,187	0,969	0,478	0,458	0,602	0,684	0,738	0,740	0,682	0,754	0,752	0,662	0,790	0,503	0,636	0,787	0,874
Greece	0,874	0,174	0,847	0,608	0,306	0,676	0,671	0,805	0,716	0,656	0,744	0,848	0,785	0,781	0,586	0,616	0,674	0,806
Hong Kong	0,857	0,268	0,792	0,543	0,378	0,808	0,610	0,737	0,705	0,717	0,740	0,791	0,767	0,910	0,526	0,742	0,762	0,866
Hungary	1,000	0,088	0,876	0,659	0,390	0,709	0,733	0,801	0,788	0,671	0,863	0,906	0,796	0,861	0,536	0,604	0,747	0,896
Indonesia	0,088	1,000	0,214	0,229	-0,183	0,301	0,303	0,362	-0,213	0,291	-0,123	0,082	0,127	0,369	0,615	0,552	-0,068	0,067
Ireland	0,876	0,214	1,000	0,541	0,448	0,655	0,713	0,810	0,742	0,745	0,764	0,816	0,722	0,819	0,563	0,671	0,772	0,886
Italy	0,659	0,229	0,541	1,000	0,225	0,568	0,747	0,745	0,277	0,381	0,675	0,749	0,709	0,647	0,494	0,555	0,294	0,528
Mexico	0,390	-0,183	0,448	0,225	1,000	0,338	0,185	0,303	0,493	0,478	0,519	0,386	0,317	0,374	0,097	0,379	0,482	0,583
Malaysia	0,709	0,301	0,655	0,568	0,338	1,000	0,542	0,682	0,518	0,603	0,615	0,687	0,728	0,828	0,440	0,655	0,594	0,710
Netherlands	0,733	0,303	0,713	0,747	0,185	0,542	1,000	0,748	0,358	0,521	0,654	0,758	0,691	0,672	0,626	0,589	0,397	0,612
Norway	0,801	0,362	0,810	0,745	0,303	0,682	0,748	1,000	0,506	0,664	0,672	0,826	0,788	0,802	0,652	0,768	0,578	0,745
New Zealand	0,788	-0,213	0,742	0,277	0,493	0,518	0,358	0,506	1,000	0,574	0,711	0,691	0,531	0,681	0,254	0,397	0,844	0,864
Philippines	0,671	0,291	0,745	0,381	0,478	0,603	0,521	0,664	0,574	1,000	0,532	0,687	0,590	0,702	0,708	0,741	0,543	0,751
Poland	0,863	-0,123	0,764	0,675	0,519	0,615	0,654	0,672	0,711	0,532	1,000	0,801	0,762	0,719	0,295	0,484	0,681	0,824
Portugal	0,906	0,082	0,816	0,749	0,386	0,687	0,758	0,826	0,691	0,687	0,801	1,000	0,824	0,825	0,600	0,672	0,630	0,815
Sweden	0,796	0,127	0,722	0,709	0,317	0,728	0,691	0,788	0,531	0,590	0,762	0,824	1,000	0,704	0,425	0,567	0,583	0,728
Singapore	0,861	0,369	0,819	0,647	0,374	0,828	0,672	0,802	0,681	0,702	0,719	0,825	0,704	1,000	0,630	0,796	0,701	0,851
Turkey	0,536	0,615	0,563	0,494	0,097	0,440	0,626	0,652	0,254	0,708	0,295	0,600	0,425	0,630	1,000	0,703	0,217	0,490
Taiwan	0,604	0,552	0,671	0,555	0,379	0,655	0,589	0,768	0,397	0,741	0,484	0,672	0,567	0,796	0,703	1,000	0,496	0,653
United States	0,747	-0,068	0,772	0,294	0,482	0,594	0,397	0,578	0,844	0,543	0,681	0,630	0,583	0,701	0,217	0,496	1,000	0,887
World	0,896	0,067	0,886	0,528	0,583	0,710	0,612	0,745	0,864	0,751	0,824	0,815	0,728	0,851	0,490	0,653	0,887	1,000

Table 13: Country weekly MSCI Total Return Index log returns Pearson correlation matrix

	Argentina	Austria	Australia	Belgium	Brazil	Canada	Switzerland	Chile	Colombia	Czech Republic	Germany	Denmark	Spain	Finland	France	United Kingdom	Greece	Hong Kong
Argentina	1,000	0,488	-0,197	0,762	0,153	-0,210	-0,467	0,770	0,412	0,052	0,098	-0,322	0,631	-0,232	-0,160	0,212	0,737	-0,155
Austria	0,488	1,000	0,609	0,710	0,401	0,611	0,304	0,457	0,386	0,847	0,735	0,395	0,845	0,564	0,692	0,897	0,575	0,575
Australia	-0,197	0,609	1,000	0,136	0,314	0,970	0,868	-0,252	-0,103	0,798	0,898	0,873	0,395	0,920	0,965	0,771	-0,039	0,857
Belgium	0,762	0,710	0,136	1,000	0,497	0,059	-0,263	0,784	0,698	0,317	0,336	-0,193	0,906	0,021	0,169	0,601	0,885	0,172
Brazil	0,153	0,401	0,314	0,497	1,000	0,185	0,033	0,405	0,644	0,360	0,208	-0,055	0,577	0,131	0,280	0,557	0,420	0,441
Canada	-0,210	0,611	0,970	0,059	0,185	1,000	0,904	-0,330	-0,205	0,825	0,888	0,918	0,314	0,925	0,968	0,739	-0,101	0,793
Switzerland	-0,467	0,304	0,868	-0,263	0,033	0,904	1,000	-0,627	-0,458	0,624	0,752	0,967	-0,003	0,889	0,875	0,466	-0,356	0,713
Chile	0,770	0,457	-0,252	0,784	0,405	-0,330	-0,627	1,000	0,740	0,067	-0,053	-0,536	0,675	-0,288	-0,218	0,288	0,722	-0,034
Colombia	0,412	0,386	-0,103	0,698	0,644	-0,205	-0,458	0,740	1,000	0,189	-0,104	-0,496	0,634	-0,248	-0,085	0,444	0,705	0,042
Czech Republic	0,052	0,847	0,798	0,317	0,360	0,825	0,624	0,067	0,189	1,000	0,745	0,650	0,554	0,773	0,866	0,883	0,182	0,720
Germany	0,098	0,735	0,898	0,336	0,208	0,888	0,752	-0,053	-0,104	0,745	1,000	0,828	0,543	0,901	0,921	0,771	0,165	0,787
Denmark	-0,322	0,395	0,873	-0,193	-0,055	0,918	0,967	-0,536	-0,496	0,650	0,828	1,000	0,061	0,930	0,884	0,480	-0,313	0,707
Spain	0,631	0,845	0,395	0,906	0,577	0,314	-0,003	0,675	0,634	0,554	0,543	0,061	1,000	0,287	0,435	0,799	0,799	0,452
Finland	-0,232	0,564	0,920	0,021	0,131	0,925	0,889	-0,288	-0,248	0,773	0,901	0,930	0,287	1,000	0,945	0,665	-0,144	0,835
France	-0,160	0,692	0,965	0,169	0,280	0,968	0,875	-0,218	-0,085	0,866	0,921	0,884	0,435	0,945	1,000	0,815	0,018	0,858
United Kingdom	0,212	0,897	0,771	0,601	0,557	0,739	0,466	0,288	0,444	0,883	0,771	0,480	0,799	0,665	0,815	1,000	0,467	0,749
Greece	0,737	0,575	-0,039	0,885	0,420	-0,101	-0,356	0,722	0,705	0,182	0,165	-0,313	0,799	-0,144	0,018	0,467	1,000	0,002
Hong Kong	-0,155	0,575	0,857	0,172	0,441	0,793	0,713	-0,034	0,042	0,720	0,787	0,707	0,452	0,835	0,858	0,749	0,002	1,000
Hungary	0,078	0,800	0,798	0,376	0,586	0,780	0,608	0,081	0,240	0,882	0,741	0,611	0,638	0,714	0,835	0,871	0,263	0,771
Indonesia	0,417	0,564	0,332	0,645	0,731	0,219	0,005	0,505	0,689	0,451	0,286	-0,021	0,721	0,129	0,300	0,616	0,592	0,377
Ireland	-0,099	0,561	0,916	0,098	0,057	0,921	0,857	-0,306	-0,294	0,669	0,947	0,922	0,326	0,919	0,912	0,643	-0,044	0,738
Italy	0,060	0,805	0,906	0,388	0,405	0,888	0,741	0,001	0,100	0,856	0,929	0,766	0,622	0,861	0,954	0,885	0,261	0,841
Mexico	0,573	0,856	0,470	0,804	0,399	0,437	0,112	0,509	0,468	0,634	0,585	0,201	0,893	0,369	0,495	0,777	0,688	0,376
Malaysia	0,530	0,534	0,078	0,668	0,482	-0,034	-0,250	0,783	0,673	0,294	0,255	-0,179	0,662	0,106	0,128	0,460	0,603	0,292
Netherlands	-0,284	0,503	0,931	-0,089	0,048	0,966	0,957	-0,448	-0,378	0,747	0,867	0,982	0,179	0,948	0,941	0,605	-0,223	0,770
Norway	0,048	0,852	0,840	0,371	0,397	0,846	0,617	0,128	0,200	0,949	0,822	0,655	0,597	0,816	0,891	0,907	0,189	0,793
New Zealand	-0,631	-0,055	0,691	-0,456	-0,032	0,671	0,870	-0,709	-0,498	0,278	0,547	0,818	-0,240	0,719	0,641	0,170	-0,520	0,590
Philippines	0,567	0,531	0,213	0,744	0,659	0,110	-0,115	0,560	0,657	0,315	0,233	-0,121	0,744	0,001	0,184	0,528	0,669	0,249
Poland	0,729	0,701	0,055	0,854	0,590	-0,004	-0,299	0,831	0,733	0,402	0,216	-0,246	0,847	-0,006	0,116	0,570	0,781	0,185
Portugal	-0,331	0,468	0,891	-0,050	0,105	0,892	0,913	-0,390	-0,240	0,687	0,853	0,915	0,211	0,925	0,917	0,612	-0,172	0,793
Sweden	-0,187	0,546	0,935	-0,002	0,053	0,962	0,916	-0,375	-0,368	0,726	0,913	0,964	0,260	0,946	0,935	0,627	-0,159	0,766
Singapore	0,150	0,826	0,745	0,517	0,642	0,685	0,469	0,287	0,436	0,835	0,719	0,465	0,732	0,647	0,789	0,929	0,412	0,827
Turkey	0,859	0,267	-0,369	0,723	0,235	-0,430	-0,605	0,732	0,486	-0,216	-0,118	-0,519	0,559	-0,450	-0,357	0,042	0,791	-0,294
Taiwan	-0,345	0,405	0,902	-0,177	-0,024	0,929	0,952	-0,508	-0,465	0,653	0,833	0,981	0,083	0,924	0,892	0,508	-0,313	0,740
United States	-0,426	0,391	0,908	-0,219	0,030	0,946	0,980	-0,548	-0,410	0,705	0,794	0,975	0,049	0,928	0,912	0,537	-0,345	0,748
World	-0,368	0,459	0,935	-0,140	0,078	0,965	0,972	-0,484	-0,355	0,743	0,838	0,974	0,131	0,946	0,942	0,600	-0,274	0,782

(continuation)

	Hungary	Indonesia	Ireland	Italy	Mexico	Malaysia	Netherlands	Norway	New Zealand	Philippines	Poland	Portugal	Sweden	Singapore	Turkey	Taiwan	United States	World
Argentina	0,078	0,417	-0,099	0,060	0,573	0,530	-0,284	0,048	-0,631	0,567	0,729	-0,331	-0,187	0,150	0,859	-0,345	-0,426	-0,368
Austria	0,800	0,564	0,561	0,805	0,856	0,534	0,503	0,852	-0,055	0,531	0,701	0,468	0,546	0,826	0,267	0,405	0,391	0,459
Australia	0,798	0,332	0,916	0,906	0,470	0,078	0,931	0,840	0,691	0,213	0,055	0,891	0,935	0,745	-0,369	0,902	0,908	0,935
Belgium	0,376	0,645	0,098	0,388	0,804	0,668	-0,089	0,371	-0,456	0,744	0,854	-0,050	-0,002	0,517	0,723	-0,177	-0,219	-0,140
Brazil	0,586	0,731	0,057	0,405	0,399	0,482	0,048	0,397	-0,032	0,659	0,590	0,105	0,053	0,642	0,235	-0,024	0,030	0,078
Canada	0,780	0,219	0,921	0,888	0,437	-0,034	0,966	0,846	0,671	0,110	-0,004	0,892	0,962	0,685	-0,430	0,929	0,946	0,965
Switzerland	0,608	0,005	0,857	0,741	0,112	-0,250	0,957	0,617	0,870	-0,115	-0,299	0,913	0,916	0,469	-0,605	0,952	0,980	0,972
Chile	0,081	0,505	-0,306	0,001	0,509	0,783	-0,448	0,128	-0,709	0,560	0,831	-0,390	-0,375	0,287	0,732	-0,508	-0,548	-0,484
Colombia	0,240	0,689	-0,294	0,100	0,468	0,673	-0,378	0,200	-0,498	0,657	0,733	-0,240	-0,368	0,436	0,486	-0,465	-0,410	-0,355
Czech Republic	0,882	0,451	0,669	0,856	0,634	0,294	0,747	0,949	0,278	0,315	0,402	0,687	0,726	0,835	-0,216	0,653	0,705	0,743
Germany	0,741	0,286	0,947	0,929	0,585	0,255	0,867	0,822	0,547	0,233	0,216	0,853	0,913	0,719	-0,118	0,833	0,794	0,838
Denmark	0,611	-0,021	0,922	0,766	0,201	-0,179	0,982	0,655	0,818	-0,121	-0,246	0,915	0,964	0,465	-0,519	0,981	0,975	0,974
Spain	0,638	0,721	0,326	0,622	0,893	0,662	0,179	0,597	-0,240	0,744	0,847	0,211	0,260	0,732	0,559	0,083	0,049	0,131
Finland	0,714	0,129	0,919	0,861	0,369	0,106	0,948	0,816	0,719	0,001	-0,006	0,925	0,946	0,647	-0,450	0,924	0,928	0,946
France	0,835	0,300	0,912	0,954	0,495	0,128	0,941	0,891	0,641	0,184	0,116	0,917	0,935	0,789	-0,357	0,892	0,912	0,942
United Kingdom	0,871	0,616	0,643	0,885	0,777	0,460	0,605	0,907	0,170	0,528	0,570	0,612	0,627	0,929	0,042	0,508	0,537	0,600
Greece	0,263	0,592	-0,044	0,261	0,688	0,603	-0,223	0,189	-0,520	0,669	0,781	-0,172	-0,159	0,412	0,791	-0,313	-0,345	-0,274
Hong Kong	0,771	0,377	0,738	0,841	0,376	0,292	0,770	0,793	0,590	0,249	0,185	0,793	0,766	0,827	-0,294	0,740	0,748	0,782
Hungary	1,000	0,606	0,654	0,877	0,631	0,291	0,705	0,867	0,335	0,484	0,473	0,672	0,694	0,880	-0,058	0,611	0,645	0,691
Indonesia	0,606	1,000	0,126	0,464	0,595	0,571	0,081	0,431	-0,087	0,904	0,708	0,122	0,105	0,653	0,442	0,007	0,027	0,084
Ireland	0,654	0,126	1,000	0,858	0,435	0,025	0,935	0,724	0,704	0,065	-0,054	0,893	0,965	0,583	-0,298	0,929	0,890	0,914
Italy	0,877	0,464	0,858	1,000	0,625	0,310	0,838	0,895	0,497	0,360	0,316	0,847	0,848	0,874	-0,104	0,774	0,776	0,824
Mexico	0,631	0,595	0,435	0,625	1,000	0,456	0,309	0,627	-0,196	0,628	0,712	0,257	0,398	0,638	0,447	0,227	0,182	0,251
Malaysia	0,291	0,571	0,025	0,310	0,456	1,000	-0,114	0,384	-0,259	0,519	0,743	0,049	-0,071	0,532	0,440	-0,170	-0,175	-0,113
Netherlands	0,705	0,081	0,935	0,838	0,309	-0,114	1,000	0,755	0,765	-0,031	-0,143	0,923	0,981	0,584	-0,489	0,980	0,981	0,989
Norway	0,867	0,431	0,724	0,895	0,627	0,384	0,755	1,000	0,328	0,300	0,416	0,734	0,757	0,872	-0,215	0,671	0,709	0,754
New Zealand	0,335	-0,087	0,704	0,497	-0,196	-0,259	0,765	0,328	1,000	-0,235	-0,520	0,818	0,720	0,235	-0,646	0,815	0,829	0,805
Philippines	0,484	0,904	0,065	0,360	0,628	0,519	-0,031	0,300	-0,235	1,000	0,746	-0,017	0,016	0,532	0,571	-0,109	-0,111	-0,050
Poland	0,473	0,708	-0,054	0,316	0,712	0,743	-0,143	0,416	-0,520	0,746	1,000	-0,113	-0,086	0,548	0,637	-0,259	-0,251	-0,180
Portugal	0,672	0,122	0,893	0,847	0,257	0,049	0,923	0,734	0,818	-0,017	-0,113	1,000	0,897	0,619	-0,468	0,910	0,922	0,936
Sweden	0,694	0,105	0,965	0,848	0,398	-0,071	0,981	0,757	0,720	0,016	-0,086	0,897	1,000	0,577	-0,400	0,973	0,948	0,963
Singapore	0,880	0,653	0,583	0,874	0,638	0,532	0,584	0,872	0,235	0,532	0,548	0,619	0,577	1,000	0,013	0,490	0,528	0,586
Turkey	-0,058	0,442	-0,298	-0,104	0,447	0,440	-0,489	-0,215	-0,646	0,571	0,637	-0,468	-0,400	0,013	1,000	-0,521	-0,617	-0,563
Taiwan	0,611	0,007	0,929	0,774	0,227	-0,170	0,980	0,671	0,815	-0,109	-0,259	0,910	0,973	0,490	-0,521	1,000	0,975	0,976
United States	0,645	0,027	0,890	0,776	0,182	-0,175	0,981	0,709	0,829	-0,111	-0,251	0,922	0,948	0,528	-0,617	0,975	1,000	0,996
World	0,691	0,084	0,914	0,824	0,251	-0,113	0,989	0,754	0,805	-0,050	-0,180	0,936	0,963	0,586	-0,563	0,976	0,996	1,000

Table 14: Regression results for models (3) and (5) using both same week and lagged music sentiment, for different time factors, while adding a dummy variable to capture for positive months (equal to 1 for January and March in Northern Hemisphere countries, January and September for Southern Hemisphere countries) and another for negative months (equal to 1 for September and October for Northern Hemisphere countries, March and April for Southern Hemisphere countries). The dependent variable is weekly log returns of the MSCI Total Return Index (in %). White-corrected t-test statistics in parenthesis. The 10%, 5% and 1% significant levels are represented by *, **, and ***, respectively.

	(3)		(5)		(3)		(5)	
$\Delta SWAV_t$	-19,691	(-6,908)***	-3.773	(-1.726)*	-17,586	(-6,201)***	-4.691	(-2.109)**
$\Delta SWAV_{t-1}$	3,864	(1,358)	4.300	(1.960)*	5,258	(1,887)*	2.202	(1.003)
R_{t-1}			-0.013	(-1.076)			-0.039	(-3.143)***
R_{world}			1.044	(40.994)***			1.024	(37.258)***
ΔEPU			0.348	(-3.874)***			-0.299	(-3.166)***
ΔVIX			0.009	(0.036)			0.177	(0.697)
ΔADS			0.024	(0.290)			0.093	(0.619)
$Positive$	-0,093	(-0,385)	-0.106	(-0.542)	-0,096	(-0,406)	-0.103	(-0.532)
$Negative$	-0,312	(-1,898)*	-0.291	(-2.108)**	-0,307	(-1,911)*	-0.300	(-2.174)**
Factors	Country, Month		Country, Month		Country, YearMonth		Country, YearMonth	
Adj. R^2	0,029		0,383		0,120		0,400	
Obs	9098		9096		9098		9096	
df	9048		9041		9000		8993	

Table 15: Regression results for models (3) and (5) using both same week and lagged music sentiment, for different time factors, changing the time period from the week ending on Thursday, January 5th, 2017, until the 31st of December, 2020, a timeframe more similar to Edmans et al. (2021). The dependent variable is weekly log returns of the MSCI Total Return Index (in %). White-corrected t-test statistics in parenthesis. The 10%, 5% and 1% significant levels are represented by *, **, and ***, respectively.

	(3)		(5)		(3)		(5)	
$\Delta SWAV_t$	-20,318	(-6,027)***	-4,035	(-1,609)	-16,471	(-4,975)***	-5,207	(-1,853)*
$\Delta SWAV_{t-1}$	3,304	(0,968)	4,801	(1,890)*	6,294	(1,910)*	2,949	(1,067)
R_{t-1}			-0,012	(-0,890)			-0,037	(-3,760)***
R_{world}			1,065	(39,547)***			1,061	(42,504)***
ΔEPU			-0,360	(-3,714)***			-0,326	(-3,144)***
ΔVIX			-0,250	(-0,917)			0,009	(0,034)
ΔADS			-0,116	(-1,284)			-0,413	(-3,113)***
Factors	Country, Month		Country, Month		Country, YearMonth		Country, YearMonth	
Adj. R^2	0,045		0,417		0,130		0,435	
Obs	7278		7276		7278		7276	
df	7238		7223		7194		7178	