Unsettled Times: Music Discovery Reveals Divergent Cultural Responses to War

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Abstract

Societal disruption can lead to cultural innovation and transformation, but understanding how cultural practices such as music evolve in response to crisis remains a key challenge. Here, we investigate the impact of war on culture by analyzing millions of daily music discoveries across 1,423 cities in 53 countries during the 2022 Russian invasion of Ukraine. Cultural responses varied significantly across countries, cities, and demographics. In Ukraine, the war triggered a rapid rise in local patriotic music, while in Russia, it led to a decline in engagement with local culture. In Belarus, despite its political alliance with Russia, we observed increased discovery of pro-Ukrainian music, suggesting resistance. Within-country variations were correlated with latent subnational socio-cultural divides between cities, indicating that local context and demographics shaped patterns of response. Despite these differences, cultural changes showed similar dynamics: they emerged rapidly, often within days of the invasion, and then remained stable for months. These divergent responses demonstrate the contingent and contextual nature of cultural change, challenging deterministic theories and revealing processes of cultural evolution that are otherwise hidden in peacetime.

Introduction

War generates one of the most severe forms of disruption and instability in the social fabric. The 2022 Russian invasion of Ukraine epitomizes such disruption[1], with millions of refugees[2] and extensive civilian casualties[3]. As the conflict unfolded, its consequences rapidly disrupted daily routines and expectations, affecting psychological well-being[4,5] and reshaping public discourse on social media[6–9]. Cultural practices—including music, rituals, and religion—can help people cope in such times of uncertainty, sustain social cohesion, and foster supportive communities that collectively process shared experiences[10–15]. Here, we study how culture—defined as the set of socially transmitted information in a population[16,17]—changed across countries and regions during this conflict. We focus on music, a universal and ubiquitous cultural artefact[18–20] closely tied to psychological and social functions[21–23], demographic diversity[24], group identity[25–27], and collective experiences shaped by external events[28–31]. Investigating collective shifts in music engagement during crises can thus provide insights into how societies cope, innovate, and reorient themselves.

Much evidence supports the idea that war increases within-group sociality and cooperation, leading to increased conformity to social norms and engagement with local cultural practices, such as religion[32,33] and collective action[34,35]. War can also foster group identity and increase out-group hostility[36–40]. Consistently, cultural evolution theory suggests that evolutionary pressures would favor adaptive societal responses to external threats, such as increased sociality, norm adherence, and willingness to punish norm violators[41–43]. Such adaptations can be also reflected in cultural artifacts, such as music, which are thought to reinforce group identity and social bonding during times of crises[31,44,45]. In this way, war is expected to increase engagement with cultural artifacts that promote social cohesion and shared values within groups.

Yet, not all responses to crises are cohesive. Swidler's theory[46] proposes that periods of acute disruption—"unsettled times"—serve as fertile ground for rapid cultural innovation and transformation[47–49]. Disruptive events might compel societies to experiment with new "strategies of action," such as habits, skills, and practices. Consequently, the theory predicts that crises can lead to diverse kinds of cultural responses across societies, depending on the structural opportunities at hand—financial resources, institutional arrangements, social networks, and political sentiments— which together shape the actions that are adopted and implemented. For example, cultural responses may manifest not only as expressions of nationalism, but also as resistance[50,51] or collective disengagement[52]. Yet traditional approaches have struggled to capture these varied responses with fine-grained temporal and geographic resolution, especially when analyzing collective engagement with cultural artifacts like music.

Here, we examine cultural change during unsettled times by analysing data from 66.5 million daily music discoveries on Shazam, covering 1,423 cities across 53 countries during the 2022 Russian invasion of Ukraine (Fig. 1a). We assess at multiple levels how societies and regional communities respond culturally to acute social disruption. This approach allows us to empirically test whether social disruption triggers cohesive cultural responses (e.g., in-group sociality and social bonding) or leads to a broader range of engagements and rapid cultural change that reflect adaptive, context-dependent responses to uncertainty as implied by Swidler's theory.

We use data from Shazam[53], a popular mobile application that allows users to identify music playing in their surroundings by recording a short audio sample. Shazam data capture a unique combination of top-down and bottom-up cultural signals. First, it samples music played in real-world, open-air, and often public environments (e.g., bars, restaurants, social gatherings), reflecting broader cultural contexts typically influenced by social, institutional and political forces (Fig. 1b). Second, Shazam captures active, individual curiosity and engagement[54]. People primarily use Shazam when they do not know a song and want to identify it, making their discoveries spontaneous and curiosity-driven, rather than reflecting passive consumption of centrally curated content.

The hybrid nature of Shazam—combining external musical exposure with active, user-driven curiosity—makes it a unique marker to detect rapid shifts in cultural tastes and consumption, distinguishing it from on-demand streaming platforms, such as Spotify and YouTube. Indeed, industry research suggests that songs tend to peak on Shazam before they peak in radio or music streaming platforms[55], making it an early indicator of growing popularity (Fig. 1c). This phenomenon, known as the Shazam effect[56], suggests that Shazam discoveries can serve as an early indicator of emerging cultural trends, rather than a mere reflection of established popularity. Importantly, Shazam interactions are private and non-performative, capturing implicit user interest without requiring public expression. This contrasts with social media platforms, where user activity is often shaped by performativity[57,58], and can be externally controlled through policing[59] or censorship[60–62], which may be particularly pronounced in authoritarian regimes.

By analyzing millions of Shazam discovery patterns, we quantitatively investigate whether, how rapidly, and in what manner wartime conditions affect collective music engagement across nations and regions. Leveraging methods from machine learning, network science, and cultural evolution, we develop new computational measures to capture changes in different aspects of culture during conflict. Specifically, we (1) analyze the language of discovered songs as a proxy for cultural locality—the degree to which cultural engagement is rooted in local or national contexts[9]; (2) apply semantic and audio embeddings to detect shifts in lyrical themes and acoustic features[63,64]; (3) compute daily similarity scores in music discovery across countries to assess patterns of cultural divergence[65,66]; (4) adapt network-science techniques[67] to model cultural influence and diffusion between cities; and (5) examine demographic and socio-cultural correlates that may explain regional variation in cultural responses. Finally, we demonstrate that our findings generalize beyond Shazam's specific usage and demographics by replicating key results on other platforms, including YouTube, Spotify, and Google Trends, and by using census data (Comparison with other data sources in Methods). We make all data and analysis code available, along with an interactive visualization of the results, at https://musicdiscover.net.

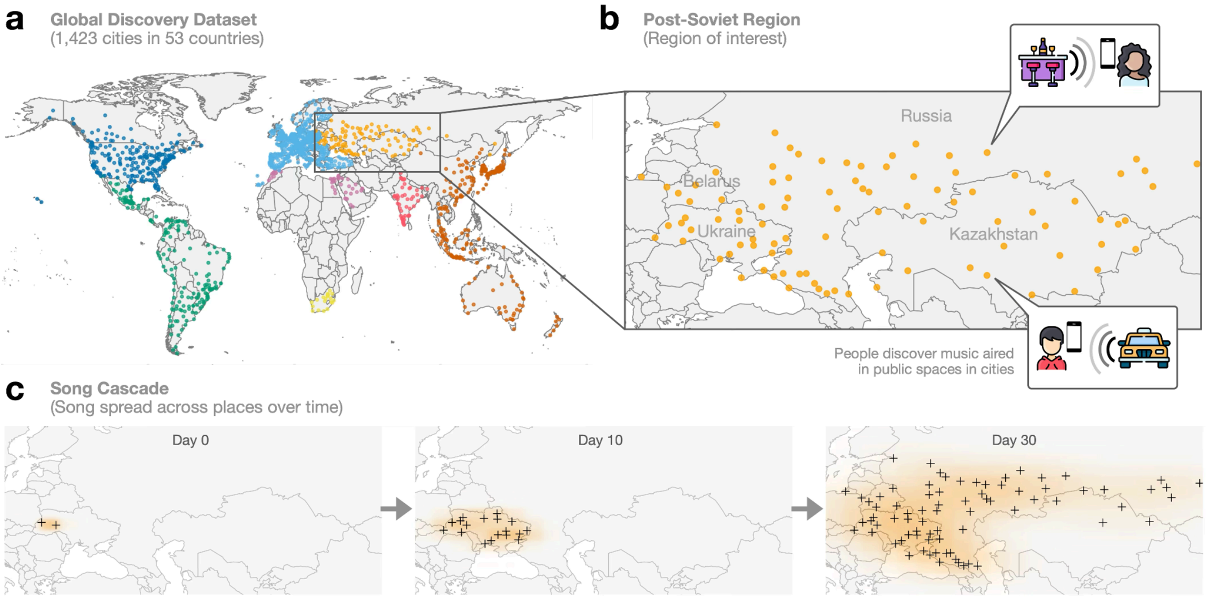


Fig. 1: Tracking global music discovery

(a) Global music discovery data across 1,423 cities and 53 countries (dots represent cities, color-coded by world region). For each city, the top 50 most discovered songs are collected every day via the popular mobile application Shazam (Dataset in Methods; see Comparison with other data sources in Methods for comparisons with another music platform and global survey data on cultural values). **(b)** Focusing on cities in the post-Soviet region, our data captures music discovered in diverse real-world environments during the onset of the 2022 Russian invasion of Ukraine. **(c)** Temporal trajectories of songs are captured as they become popular across cities over time (song cascades). As an example, we show the spread of “Stefania” by Kalush Orchestra across post-Soviet, with crosses and raster distributions indicating the cities where the song entered the local top 50 chart on days 0, 10, and 30 after its release. All data are publicly available alongside interactive visualizations at https://musicdiscover.net.

Results

Divergent responses to the war

We began by examining daily changes in music discovery patterns across post-Soviet countries (Figs. 2,3), comparing the three months before and after the Russian invasion of Ukraine that began on February 24, 2022. We used recent advances in machine learning and semantic modelling to examine changes in the content of the discovered songs, focused on language, themes, and messages conveyed in the lyrics, and the acoustic features of the music.

The rise of patriotic, local music in Ukraine and the decline of Russian music

We analyzed the proportion of songs discovered in different languages over time (Fig. 2a; Sung language in Methods). In Ukraine, the discovery of local songs (sung in Ukrainian), which was rare prior to the invasion, rapidly increased afterward, rising from 1.84% [1.74, 1.95] to 27.26% [26.92, 27.60] (Cohen's d = 4.06 [3.93, 4.19], $P < 0.001$). Notably, popular songs discovered post-invasion in Ukraine (see Table S1 for top 10) directly reflected a broad spectrum of patriotic and pro-Ukrainian sentiment, expressing themes of resistance, national identity, and emotional coping. In contrast, the proportion of songs with Russian lyrics decreased from 48.02% [47.67, 48.39] to 26.00% [25.66, 26.33] (Cohen's d = -3.10 [-3.23, -2.96], $P < 0.001$). This shift from Russian to Ukrainian music aligns with survey and social media studies that attribute recent changes in language use in Ukraine to the impact of the war, reflecting a broader shift toward national identity and away from Russian culture[9,68,69].

While we expected to see a similar trend towards local culture in Russia, the observed pattern was the opposite: the proportion of local music (sung in Russian) decreased moderately but significantly from 51.42% [51.17, 51.64] to 44.27% [44.01, 44.49] after the invasion (Cohen's d = -1.29 [-1.37, -1.22], $P < 0.001$), with even a small uptick in Ukrainian songs immediately after the invasion. This decline was progressive, reaching a low of 37.20% [34.00, 41.03] in May, three months after the invasion. Previous work has attributed similar declines in engagement with national culture to public disengagement or negative sentiment towards the war among the Russian public[8,52,70].

In Belarus, despite its political alliances with Russia, there was a significant decrease in Russian music, from 50.48% [49.80, 51.12] to 39.04% [38.34, 39.67] (Cohen's d = -1.74 [-1.94, -1.56], $P < 0.001$). Interestingly, we also see a small but significant ($P < 0.001$) surge in Ukrainian songs that were directly associated with themes of war, including pro-Ukrainian songs with anti-Russian sentiments (see Table S2 for all 15 Ukrainian songs adopted in Belarus post-invasion), suggesting undercurrents and resistance[51,71].

In Kazakhstan, we observed the least amount of change. The proportion of Russian music declined slightly from 33.58% [33.26, 33.93] to 28.04% [27.71, 28.38] after the invasion (Cohen's d = -1.44 [-1.61, -1.30], $P < 0.001$), and there was no significant change in the discovery of local music (sung in Kazakh), suggesting the war had a less pronounced impact on this population's music engagement.

We tested the stability of these findings over a longer period of two years (11/2022 - 12/2023, Fig. S1; Trend validation in Methods). We found that the elevated discovery of Ukrainian music persisted throughout this period, consistently remaining above 11.24% [9.55, 12.54], while Russian music remained below 38.82% [36.69, 41.63] and never reverted back to their pre-invasion levels. In contrast, Russian music in all other countries returned to their pre-invasion baselines within a year, suggesting a shorter-term cultural impact. These shifts could not be explained by seasonal effects (Fig. S2a), and the magnitude of change significantly exceeded typical fluctuations in music discovery trends (Fig. S2b; Trend validation in Methods).

Finally, we replicated the main country-level results using independent data from two major streaming platforms—YouTube Music and Spotify—, each with distinct user bases and platform dynamics (Fig. 2b; Spotify and YouTube Music in Methods). In both platforms, we observed a comparable rise in local music engagement in Ukraine (Spotify: Cohens'd = 2.74; YouTube: Cohen's d = 3.17; $Ps < 0.001$) and a significant decline in Russian music (Spotify: Cohens'd = -2.13; YouTube: Cohen's d = -3.35; $Ps < 0.001$), with effect sizes of similar magnitude to those observed in Shazam data. These converging results demonstrate that the observed cultural shifts are not specific to Shazam's user base or platform dynamics (see Note S1,2 for detailed user demographics and comparison across platforms).

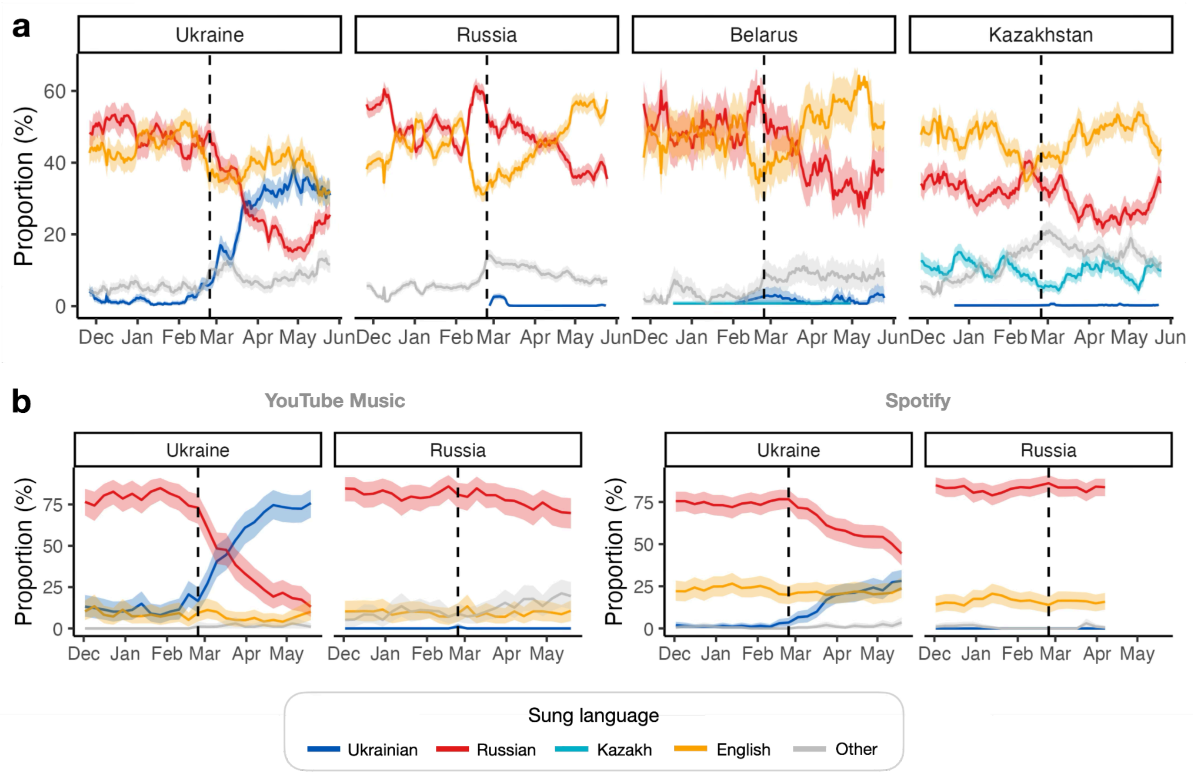


Fig. 2: Divergent cultural responses to the war.

(a) Proportion of Shazam songs discovery in different languages over time. We automatically detected the language of lyrics of all songs discovered in the post-Soviet countries using machine learning techniques (Sung language in Methods; see Figs. S1,2 for longitudinal trends and validations). The dashed line indicates the onset of the invasion. **(b)** Replication of trends on YouTube Music and Spotify. Note the data from Spotify could not be retrieved from April, presumably due to sanctions during this time. All values were derived from 1,000 bootstraps across songs on each day, with shaded ribbons corresponding to 95% CI of the bootstrap mean (Statistical analysis in Methods). Interactive visualizations can be found at https://musicdiscover.net.

Changes in song lyrics reflect topics of war in Ukraine but not in Russia

Focusing on the two countries directly involved in the war, we analyzed the semantic content of songs discovered in Ukraine (N = 2,057) and Russia (N = 769), using a Large Language Model (LLM) embedding. We extracted feature vectors for each song's lyrics and applied dimensionality reduction using UMAP to visualize semantic relationships between songs (Fig. 3a; Word embedding in Methods). The closer the two songs are in this space, the greater their semantic similarity. We further examined areas of high concentration in the distribution of local (native language) songs in Ukraine and Russia (Comparing distributions in Methods).

In Ukraine, the semantic content of local music changed drastically after the invasion (mean JSD = 0.36 [0.19, 0.52], $P < 0.001$), while in Russia, the changes were significantly smaller (mean JSD = 0.08 [0.05, 0.11], $P < 0.001$; comparison between the two: $P < 0.001$; Comparing distributions in Methods). The post-invasion Ukrainian songs were concentrated around a newly emerged area in the semantic space (Fig. 3a dashed square). Keywords that statistically appeared more frequently were related to topics of war (Fig. 3b; Keywords in Methods), such as expressions of national identity (e.g., Ukrainian, brother) and direct references to the conflict (e.g., war, armed, enemy; see Figs. S3a,b for similar results using non-translated, original language versions). In contrast, the semantic content of local music in Russia showed little qualitative difference. Moreover, the frequency of war-related songs, identified by lyrics containing top five words closely related to "war" in the embedding space (War-related songs in Methods), significantly increased in Ukraine over time ($r = 0.69$ [0.60, 0.76], $P < 0.001$), but decreased in Russia (Fig. 3c; $r = -0.33$ [-0.45, -0.19], $P < 0.001$, see Fig. S3c for validations with different number of war-related words).

Larger acoustic changes in Ukraine

Analogous to using word embeddings of lyrics, we created an acoustic embedding space through low- and mid-level acoustic features (e.g., tempo, loudness, chord change) that capture stylistic aspects of the music (Acoustic features in Methods; see Fig. S4 for acoustic UMAPs). Mirroring the changes we found in the semantic space above, songs in Ukrainian showed a significantly larger shift in their acoustics (mean JSD = 0.22 [0.06, 0.36], $P < 0.001$) compared to those in Russian (mean JSD = 0.07 [0.04, 0.10], $P < 0.001$; comparison between the two: $P < 0.001$). We next analyzed individual acoustic features by measuring the changes from pre- to post-invasion among Ukrainian and Russian songs (Fig. 3d). In general, there was not a substantial change in most individual features, but we found larger changes for Ukrainian songs after the invasion, characterized by a faster tempo (pre vs. post z-score change = 0.43 [0.20, 0.65], $P < 0.001$) and a decrease in loudness (z-score change = -0.32 [-0.48, -0.14], $P < 0.001$). These results show divergent responses not only on the semantics of the music but also its acoustics.

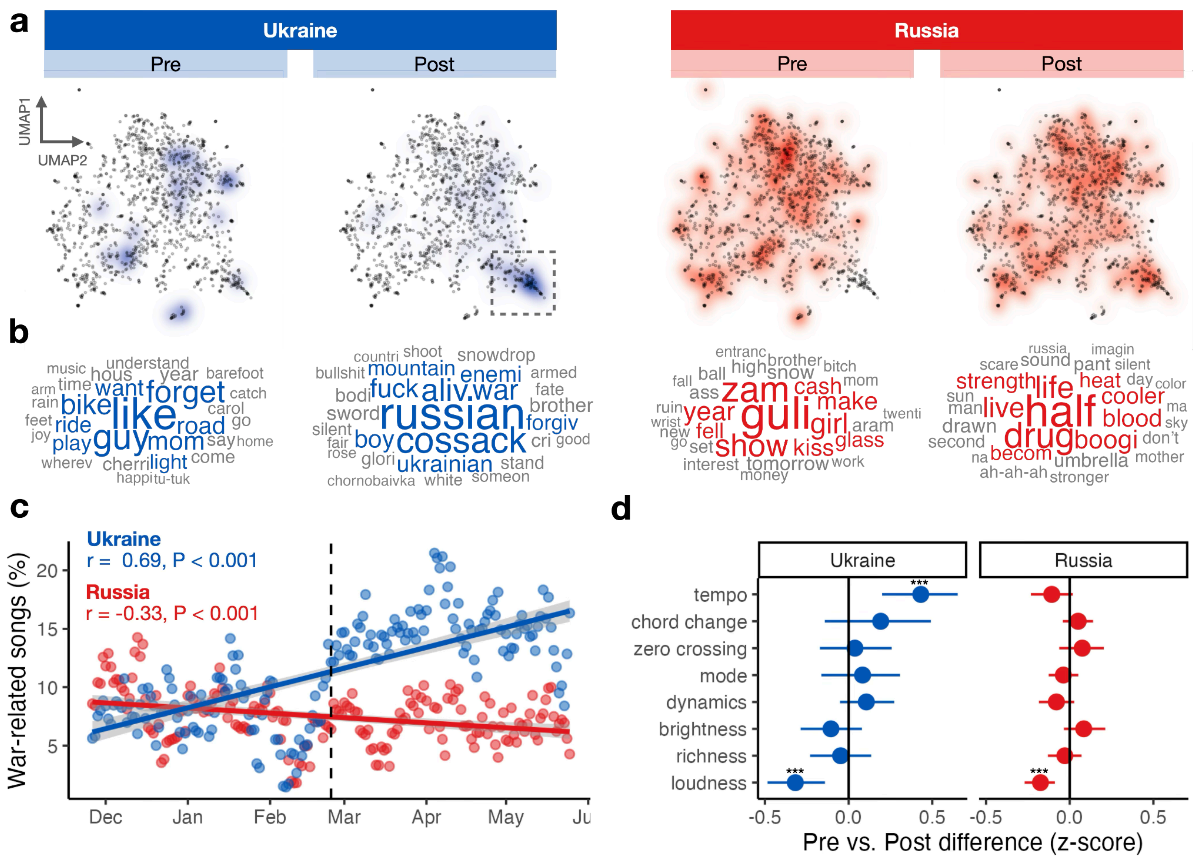


Fig. 3: Semantic and acoustic changes following invasion

(a) UMAP visualization of the lyrics semantic space across all songs discovered in Ukraine (N = 2,057) and Russia (N = 769; Word embedding in Methods). The proximity of songs in this space represents thematic similarity. Kernel density estimation (KDE) is overlaid on the general UMAP to identify areas of high local music concentration. The dashed square box in post-invasion Ukrainian songs shows the emergence of a new theme. **(c)** Word clouds of the top keywords with the top 10 words highlighted in color (Keywords in Methods; see Figs. S3a,b for keywords in non-translated versions). **(d)** Frequency of war-related songs over time, defined by song lyrics containing words related to the word "war" (War-related song in Methods; see Fig. S3c for validations). **(e)** Acoustic feature analysis comparing the difference between pre- and post-invasion songs in Ukrainian and Russian using normalized values. *** indicate significance at P = 0.001. All values were derived from 1,000 bootstraps. Shaded areas and error bars correspond to 95% CI (Statistical analysis in Methods). Interactive visualizations can be found at https://musicdiscover.net.

Variation within countries

Sampling music discovery in high spatial and temporal resolution allows us to investigate nuances of within-country variations (Within-country analysis in Methods). We analyzed these micro-variations and tested for demographic and socio-cultural correlates.

Variations in socio-cultural values predict changes in local music discovery

In both Ukraine and Russia, the spatial distribution of post-invasion shifts in local music discovery correlated with pre-existing socio-cultural values, measured using the 2017-2020 survey data from the World Value Survey (WVS) (Fig. 4a,b; World Values Survey in Methods). Our principal component analysis (PCA) of the survey responses for Ukraine and Russia showed that the first three components explained 20.69% of the variance (see Note S3 for comparison with cultural dimensions derived by Inglehart–Welzel, 2005[72]). One of these components, which explained 6.09% of the variance and related to beliefs in religion and trust in international institutions (e.g., the EU, NATO) was associated with regional variation in both countries (see Table S3 for description of components).

In Ukraine, city populations that were more religious and trusting of institutions were more likely to show an increase in local music discovery (two-tailed Spearman rho = 0.32 [0.16, 0.46], $P < 0.001$). In Russia, however, these same socio-cultural values were associated with a larger decrease in local music discovery (rho = 0.35 [0.22, 0.47], $P < 0.001$; see Fig. S5 for correlations with other components).

To examine that the within-country divide we detected in music discovery was not an artifact of characteristics of Shazam (see Note S1,2 for detailed user demographics), we replicated our results using Google Trends data on song searches, a platform with broader demographic reach, including rural areas (Google trends in Methods). The geographic pattern of Google search interest mirrored the regional variations in music discovery and revealed strong correlations with the WVS data (Two-tailed Spearman rho = 0.79, $P < 0.001$; see Fig. S6 for full description).

We found that variations within each country were also associated with underlying demographics. In Russia, the decline in local Russian music discovery was significantly larger in ethnic minority areas ($P = 0.02$; Census analysis in Methods). For example, in the southwest Tartarstan region, cities with substantial Turkic populations, such as Kazan

(31.53% Bashkr) and Ufa (53.26% Tatar), underwent declines of -11.70% [-14.05, -9.24] and -10.82% [-13.05, -8.47], respectively. Comparable declines were also observed in cities in the North Caucasus region—an area with diverse ethnic minority groups and a long history of independence movements and resistance against Russian authority[73]—including Stavropol (-11.71% [-14.07, -9.34]) and Makhachkala (-11.10% [-13.59, -8.59]). A similar trend was observed in Ukraine, where regional variation correlated significantly with demographic differences, such as language (two-tailed Spearman rho = 0.72 [0.41, 0.88], P < 0.001; Fig. S7). Namely, Ukrainian cities with larger Russian-speaking populations (who were also involved in the war, see below) exhibited smaller changes.

The impact of occupation and migration

To further understand the contribution of the course of the war itself, we examined the impact of occupation and migration on music discovery patterns across Ukrainian cities. In cities annexed by Russia in 2014, such as Donetsk, Luhansk, Kerch, and Sevastopol, where Russian is commonly spoken and the 2022 invasion had a direct impact, there was only a 4.30% [3.94, 4.66] increase in local music discovery (Cohen's d = 1.00 [0.93, 1.07], P < 0.001). In contrast, cities primarily speaking Ukrainian that were less directly affected by occupation (e.g., Kiev, Lviv) exhibited a significantly higher increase of 30.94% [30.49, 31.36] (Fig. 4c; Cohen's d = 2.83 [2.77, 2.89], P < 0.001).

An interesting exception is Mariupol (Fig. 4c dotted blue line), which is a Russian majority-speaking city that became a major battle zone during the study period[74]. The rise and fall of local (Ukrainian) music discovery aligned with the course of historical events. During the initial phase of the invasion, Mariupol experienced an increase in Ukraine music discovery, from 15.29% [2.78, 34.37] in March to 24.24% [8.11, 44.12] in April. This trend gradually reversed as fighting intensified near the city towards the end of April, and it further diminished upon the city's full occupation in May (9.32% [2.63, 25.81]), at which point it converged to the low levels seen in previously annexed cities. This pattern was potentially caused by forced migration, cultural oppression, or highly likely a combination of both, which might have occurred long before our data period in the cities that experienced war since 2014 (Donetsk and Luhansk)[75,76].

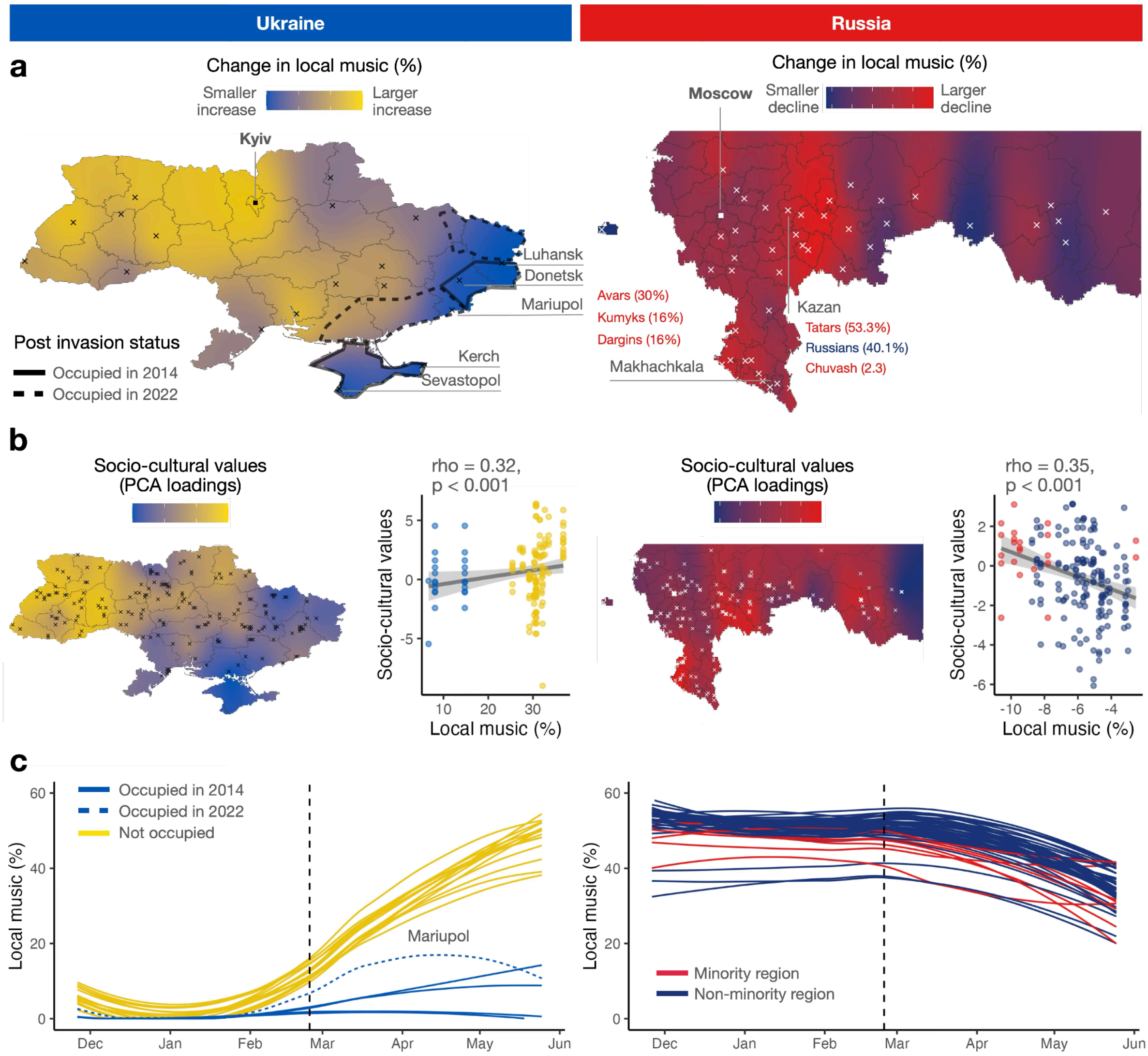


Fig. 4: Subnational trends reveal factors contributing to cultural change.

(a) City-level spatial variations in the proportion of local music within Ukraine and Russia visualized using kernel smoothing over the city locations (City trends in Methods). In Ukraine, higher values (yellow) indicate a larger increase in local music, while in Russia, higher values (red) indicate a larger decline. Occupation status in Ukraine is drawn on the map, while example regions with ethnic minority populations are labelled with census proportions in Russia (Census analysis in Methods). **(b)** Comparison of local music proportion with socio-cultural values using the World Values Survey data (World Values Survey in Methods). PCA of survey responses indicated a three-component solution, explaining 20.69% of the variability (see Table S3 for top 10 loadings per component; see Fig. S5 for correlations with all components). Results were also replicated using Google Trends (Fig. S6) and using census data (Census analysis in Methods; Fig. S7). **(c)** City-level temporal trends of local music proportion in Ukraine and Russia. The dashed vertical line indicates the onset of the invasion. The Ukrainian cities that have previously been annexed (i.e., former Crimea region) or occupied during the war (Mariupol, dotted line) by Russia are coloured in blue. The Russian cities with minority ethnic populations (less than 50% ethnic Russians) are coloured in red. All values were derived from 1,000 bootstraps. Shaded areas and error bars correspond to 95% CI (Statistical analysis in Methods).

Variation across countries

Finally, we examined the cultural impact of the war on a global scale, leveraging our entire dataset of 1,423 cities and 53 countries. This allowed us to quantify the relative magnitude of cultural change in post-Soviet countries compared to the rest of the world, as well as detect possible cultural changes beyond the post-Soviet region.

Cultural fragmentation of post-Soviet

We quantified the daily discovery similarity across countries—a measure of cultural convergence based on the overlap in song discoveries—within each world region (World regions and Discovery similarity in Methods). Previous work suggests such measures can reflect shared cultural similarities shaped by economic, social, and geopolitical factors[65,66].

We observed a rapid decline in similarity between countries within the post-Soviet region (Fig. 5a). This divergence began at least three months prior to the invasion (Generalized Additive Models (GAM) coefficient three months prior to invasion = -0.0003, 95% CI = [-0.0004, -0.0002], $P < 0.001$ via bootstrapping) and accelerated during the first month of the conflict (GAM coefficient = -0.0012 [-0.0017, -0.0008], $P < 0.001$). Compared to other world regions, the post-Soviet region showed the most pronounced decline in similarity, indicating a fragmented and divergent cultural response to the conflict across post-soviet countries (Fig. 5b; Cohen's d = -2.26 [-2.51, -2.03], $P < 0.001$).

To further investigate nuances in how these shifts affected global patterns of cultural influence, we used a network inference model[77] to reconstruct the structure of music diffusion across cities over time (Network inference in Methods). This model infers directional pathways of music diffusion (edges) between cities (nodes) based on the temporal trajectories of discovered songs.

Figures 5c,d show the global network of music diffusion before and after the invasion, using N = 79,310 song cascades (Network visualization in Methods). While the global structure of the network remained generally stable after the invasion (two-tailed Pearson r = 0.803 [0.802, 0.804], P < 0.001, Fig. S8), there was a stark shift within the post-Soviet region, where the number of network edges among the post-Soviet cities significantly decreased after the invasion by -26.76% [-27.52, -26.00]. The magnitude of this change was more than doubled that observed in any other region (Fig. S9). Prior to the conflict, post-Soviet cities were densely interconnected across national boundaries, forming a highly homogeneous cluster that exhibited the highest music discovery similarity of any region (Fig. 5c). After the invasion, however, these cities became more distant from one another (i.e., more isolated in their music discovery patterns), with the network fragmenting into distinct national clusters (Fig. 5d). This network fragmentation is consistent with our earlier finding of decreased discovery similarity in the region (Figs. 5a,b) and was replicated using a simpler co-occurrence measure (Network validation in Methods; Fig. S10).

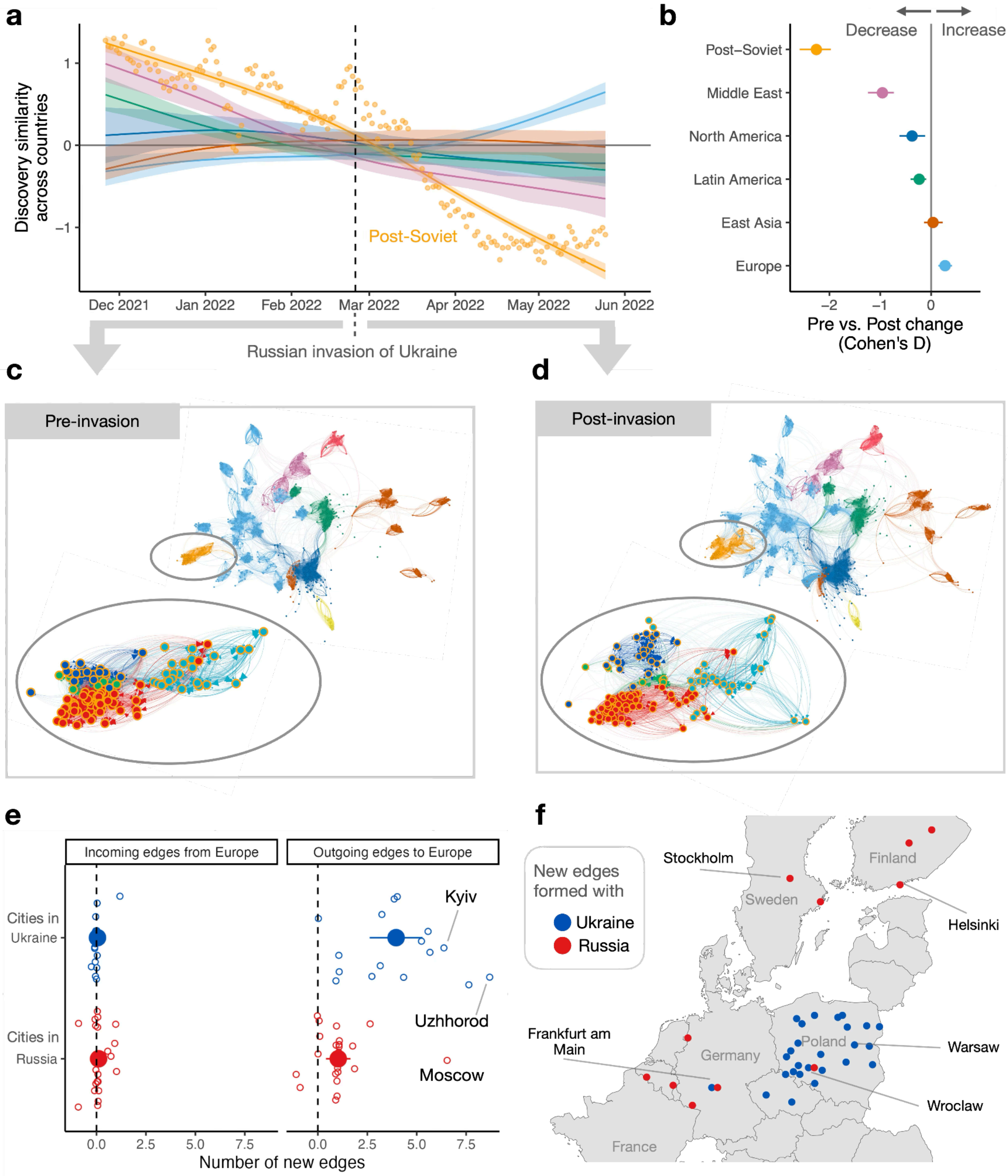
Growing cultural alignment in Europe

Beyond the divergence among post-Soviet countries, our analysis reveals a moderate but significant convergence in music discovery patterns across Europe during the same period (Fig. 5a,b); Cohen's d = 0.27 [0.14, 0.41], P < 0.001). We examine two complementary mechanisms that may explain this pattern.

One possibility is that the war fostered a sense of regional solidarity and shared identity among European countries. For example, the Eurovision-winning Ukrainian song “Stefania” by Kalush Orchestra became popular across 22 European countries after the invasion. However, beyond this single case, we found little additional evidence of large-scale diffusion of war-themed songs across Europe after the invasion (see Table S4 for a list of top songs in Europe post-invasion). This may suggest that cultural alignment may have occurred through more subtle, non-political musical expressions.

An alternative scenario is that the increased similarity may reflect shifts in the population structure of European countries due to migration[2]. Indeed, our network diffusion analysis (Network analysis in Methods) shows a significant rise in new connections between Ukrainian and European cities after the invasion (Mean number of new edges per city = 4.40 [3.80, 5.00]), with a relatively smaller change observed in Russia (M = 1.40 [1.19, 1.67]). Importantly, these new connections were unidirectional, mostly from Ukraine to Europe (Fig. 5e), and were especially concentrated in Poland (Fig. 5f), the country that hosted the largest number of Ukrainian refugees[2]. Songs discovered through these new pathways were often directly related to themes of war (see Table S5 for the top 10 Ukrainian songs adopted in Poland post-invasion), suggesting that many refugees continued engaging with their national music while in exile, thereby influencing the musical landscape of their host communities.

Taken together, these results suggest that the increased discovery similarity among European countries may stem from a combination of factors, including both subtle cultural alignment during the conflict and the lasting cultural impact of forced migration.


a
Discovery similarity across countries
1
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Post-Soviet
Dec 2021
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Jun 2022
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Middle East
North America
Latin America
East Asia
Europe
−2
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0
Pre vs. Post change (Cohen's D)
c
Pre-invasion
d
Post-invasion
e
Incoming edges from Europe
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Cities in Ukraine
Cities in Russia
Kyiv
Uzhhorod
Moscow
0.0
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New edges formed with
Ukraine
Russia
Stockholm
Finland
Sweden
Helsinki
Frankfurt am Main
Poland
Germany
Warsaw
Wroclaw
France

Fig. 5: Cultural fragmentation in the post-Soviet region, but growing alignment in Europe

(a) Music discovery similarity among countries within each world region over time (Discovery similarity in Methods). The dashed line indicates the onset of the Russian invasion of Ukraine on February 24, 2022. To visually compare across regions that have different baseline similarities, the values are normalized (z-score) for each region and GAMs are fitted for each region over the days. The horizontal dashed line at intercept 0 indicates non-significant changes. The more negative the values, the lower the discovery similarity across countries in a given region (see Table S6 for all countries and regions in our data). **(b)** Effect size comparison of average music discovery similarity change comparing pre- and post-invasion periods. **(c,d)** Inferred global network of cultural influence respectively three months before and three months after the invasion based on 79,310 song cascades (Network inference in Methods). Nodes represent cities colored by the world regions, while edges represent directional pathways of diffusion. The post-Soviet region is highlighted in a circle and zoomed in. **(e)** Number of new edges formed between cities in Ukraine and Russia from (incoming) and to (outgoing) cities in Europe after the invasion (Ukraine, Russia, and Europe section in Methods). Small circles represent the mean number of new edges formed per city. Large circles represent the country-level mean with 95% CI error bars. **(f)** Cities in Europe that received new influences (i.e., new incoming edges) from Russia and Ukraine after the invasion. A new edge was defined as an edge that exists in the post-invasion network but not in the pre-invasion network. Interactive visualization of the song's diffusion trajectories is available at https://musicdiscover.net. All values and network inference were derived from 1,000 bootstraps. Shaded areas and error bars correspond to 95% CI (Statistical analysis in Methods).

Discussion

We investigated the causal impact of war on culture by analyzing millions of daily music discoveries across 1,423 cities and 53 countries during the 2022 Russian invasion of Ukraine. We used Shazam discovery data—capturing both external musical exposure and active individual curiosity—to track shifts in collective engagement with music in real time, including changes in song language, lyrical and acoustic content, and patterns of cultural similarity and diffusion across countries, cities, and demographics.

Our findings reveal a complex and fragmented landscape of cultural reactions to the war (Fig. 2). In Ukraine, the invasion triggered a rapid and abrupt rise in patriotic music, with local Ukrainian songs quickly replacing much of the previously popular Russian repertoire. Semantic and acoustic analyses confirmed that these songs differed significantly from pre-invasion content, including explicit references to war, national identity, and expressions of resistance (Figs. 3a-c; see Table S1 for top 10 Ukrainian songs post-invasion). Indeed, most of these songs, such as Вова, їбаш їх блять ("Vova, fucking fight them") and Буде весна ("Spring will come"), have become anthems of hope for Ukrainians, played at anti-war demonstrations and gaining substantial traction on social media[78–80]. This shift from Russian to Ukraine culture aligns with broader changes in language use documented in survey and social media studies[9,68,69], which link the war to an increase in Ukrainian-language expression and national identity, alongside a reduction in Russian-language media and culture.

These results are consistent with much evidence suggesting that exposure to war increases in-group sociality and engagement with local culture[37,39,81–86]. However, our study extends this work by showing that war can also increase engagement with specific cultural artifacts—such as music—that explicitly promote social cohesion and shared values within groups. This supports the hypothesis that music serves an adaptive social function by reinforcing social bonds during collective threats[45,87], highlighting its role not just as a reflection of cultural tastes and preferences, but also as an active tool for strengthening group identity, motivating collective action, and fostering psychological resilience[11,26,31].

However, we did not observe the same pattern of increased national culture in all countries. In Russia, we found the opposite trend: a significant decline in engagement with their local culture and war-related content. This form of collective disengagement could potentially reflect different mechanisms, including government censorship and media control[5,88], negative public sentiment towards the war[8,70], or broader social withdrawal, apathy, or ambivalence[52]. Crucially, this response was not homogeneous across Russia. (Fig. 4a,b). Cities with more ethnically diverse populations, younger demographics, or weaker historical alignment with pro-Kremlin ideology showed especially pronounced declines in Russian music discovery after the war. These trends suggest that disengagement may not simply reflect indifference, but could instead represent more complex reactions that depend on local political and social contexts[52].

Interestingly, Belarus showed both a significant decrease in the discovery of Russian music and an increase in the discovery of war-related Ukrainian music shortly after the start of the invasion, possibly reflecting undercurrents of cultural resistance that diverge from the nation's official political stance[51,71]. Previous work has documented censorship of cultural production in Belarus, including restrictions on live concerts by protest musicians and tight media control over cultural expression[89]. Our results support previous research showing that authoritarian contexts often foster hidden or subcultural forms of dissent, expressed through cultural practices in art[90].

Despite the differences in the nature of cultural responses across post-Soviet countries, our analysis uncovered a consistent pattern in the temporal dynamics: cultural shifts occurred at remarkable speed, solidifying just within weeks after the onset of the invasion (Fig. 2a,b; see Figs. S6 for replications on Google). While previous research typically characterizes cultural change in music as a slow, generational process, such as shifts in music diversity[91,92] or music genres and styles[63,93,94], our findings show that certain elements of music can shift much more rapidly in response to acute disruption. This suggests that unlike core structural elements (i.e., tonal systems in music) that may change gradually, more surface-level features such as lyrics, acoustics, and stylistic preferences can be highly responsive to external shocks. These rapid dynamics align with social media studies showing how digital traces can inform real-world events such as natural disasters[95–97], pathogen outbreaks[98–100], and political movements[101–103]. However, our study goes beyond the realm of social media activity and discourse to probe culture more directly, capturing not just what people say, but how they engage with cultural artifacts in their immediate surroundings.

Unsettled times

Our findings align with Swidler's distinction between "settled" and "unsettled" times[46]. In settled periods, people rely implicitly on established cultural repertoires to guide everyday behavior, whereas unsettled times—such as those marked by social disruption—create opportunities for new cultural practices to emerge[47–49]. Indeed, our data showed that post-Soviet countries directly affected by the war experienced the largest shifts in music discovery patterns, in contrast to more "settled" nations where cultural patterns remained largely stable (Fig. 5).

Swidler's theory also emphasizes that periods of disruption often trigger ideological struggles, but the specific cultural forms that emerge depend on the structural opportunities available in each society, such as resources, institutions, and social values and networks[46,48]. This implies that the adopted cultural practices can vary markedly across local contexts (in our case countries and regions). Our findings illustrate this in two important ways. First, the cultural disengagement observed in Russia and the unexpected rise of pro-Ukrainian music in Belarus exemplify how different structural conditions produced divergent outcomes, ranging from withdrawal to resistance (Figs. 2,3). Second, variation in music discovery within countries was correlated with pre-existing socio-cultural values and historical factors that were not apparent before the war (Fig. 4). In Russia, regional differences corresponded to known socio-cultural divides, including urban-rural splits and ethnic composition, while in Ukraine, variation aligned with language use and proximity to the conflict zone.

Together, the spectrum of cultural responses we observed, and the way in which they develop across and within nations, provide strong empirical support to Swidler's core argument: that culture is not a fixed set of pre-established routines and values but a dynamic resource (or "toolkit") that adapts to contextual pressures (those shaped by local institutions, demographic, and ideological conditions). This has important implications for evolutionary theories of music, such as those proposed by social bonding theory[87], which argue that music's primarily adaptive function is to promote in-group cohesion and sociality. Instead, the presence of these responses in some contexts but not in others suggests a more nuanced perspective. Rather than viewing music as a universal or deterministic mechanism for cohesion, our results suggest that music's role is contingent on the specific structural, ideological, and emotional landscapes in which it is embedded. Music, in this view, is not merely a product of evolutionarily hardwired social functions, but a flexible cultural resource that adapts dynamically to the particular conditions of each context.

Limitations and future directions

Our study has several limitations. First, our data is limited to Shazam users, who may not fully represent the general population. For example, our data does not cover certain geographical regions in the global south and is limited to post-Soviet countries where Shazam data is available. Moreover, Shazam's user demographics are predominantly young and relatively male-skewed compared to other major platforms like Spotify and YouTube (Notes S1,2; Spotify and YouTube Music in Methods). To address this, we replicated the key results of our study—including country-level trends in local music consumption—using data from YouTube and Spotify, demonstrating that our findings are not specific to Shazam's user base (Fig. 2b). We also replicated our results at both country and city levels using data from

Google Trends (Google trends in Method), which has a broader demographic reach, including rural populations and older age groups (Fig. S6). These converging results across platforms demonstrate that the observed shifts in Shazam discovery data reflect genuine population-level changes rather than platform-specific biases.

These cross-platform comparisons also address potential concerns that data from commercial services, such as Shazam, may be influenced by endogenous factors beyond user behavior, including algorithm recommendations, system drift, or commercial goals, which can shape macro-level trends in music consumption. In addition, we show that our results are robust to alternative explanations of cultural change, including seasonal effects (Fig. S2a) and general fluctuations in music trends over time (Fig. S2b). Future research could further explore these issues through industry-academic collaborations, which provide access to high-resolution, individual-level data, enabling tests of cultural evolution at an unprecedented scale[24,28,104].

An additional limitation is that traditional or culturally niche music may be underrepresented in Shazam data. Our analysis on release dates of songs suggests that the majority of popular songs on Shazam were released within the last decade, with almost no songs before the 1990s (see Fig. S11 for full histogram of Ukrainian and Russian songs). Moreover, we show that Shazam captures music that is different from popular music streaming platforms, such as Spotify and YouTube (see Spotify and YouTube Music in Methods for comparison in overlapping songs across platforms). Future research could further address this issue by employing alternative monitoring methods, such as analyzing raw audio streams from local radio broadcasts, providing a more comprehensive coverage of diverse musical styles.

Shazam's ability to detect emergent cultural trends—popularly known as the *Shazam effect*[56]—stems from its dual nature: it captures both music played in public or open-air settings and the spontaneous curiosity of individual users. However, based on Shazam data alone, it is difficult to disentangle the influence of top-down forces (e.g., state-controlled media, propaganda, prevailing ideologies) from bottom-up processes (e.g., personal interests, preferences, or values). In authoritarian regimes, top-down forces often dominate, with censorship suppressing public expression and masking cultural change. Yet, our findings in Belarus and Russia show music discovery patterns that diverge from official narratives, suggesting an important role of individual agency and preferences. Still, Shazam discoveries can be driven by a wide range of motivations—not only interest or preference, but also disapproval or resistance. Future research could incorporate surveys to better understand the motivations behind song discovery, especially in unsettled or repressive environments.

Finally, we infer statistically reliable changes in relation to the onset of the invasion, but we cannot experimentally test for causal links[105]. However, by continuously monitoring collective cultural engagement during an event that was accidental, we can conceptualize our study as a natural experiment, allowing for causal insight into large-scale controlled experiments that would otherwise not be feasible[106]. Causal manipulation can be explored more directly in large-scale experimental setups, which allow the simulation of complex cultural dynamics with human participants in highly controlled settings, such as artificial social networks[107,108] and cultural transmission experiments[109,110].

More broadly, our work demonstrates the benefits of combining recent advances in information and computational technology with a large-scale natural experiment to quantitatively analyze the dynamics of cultural change during war. We show how music can be used as a powerful tool to characterize, monitor, and even predict population-level changes in culture both globally and within nations. This approach opens new interdisciplinary research paths, combining insights from sociology, humanities, cultural evolution, and computer science to address pressing real-world issues about society and culture. For instance, contributing to the tools available to policymakers to formulate strategies that promote unity and resilience in the face of adversities. Understanding the complex dynamics of cultural shifts during times of crises significantly expands our knowledge, offering novel insights into how societal disruptions imprint the evolution of human culture.

Inclusion & Ethics

The data used in this study was obtained adhering to Shazam website's crawling limits and publicly available Terms and Conditions, which permit the use of publicly available data for non-commercial purposes (https://www.shazam.com/terms). The datasets consist of already public, anonymized, and aggregated data, and thus cannot be used to identify information of individual users or specific groups. This data collection procedure was approved under exempt status by the Ethics Council of the Max Planck Society (Application No: 2024_11). Theoretically, our research suggests the possibility of institutions using music data for surveillance. This is not possible directly from our anonymized, aggregated data and would instead require access to granular, personally identifiable information at the individual level, such as low-level network data. Indeed, studies on policing social media and communications have demonstrated how governments may directly monitor individuals' communications using such techniques[59–62]. Our study contributes to society by making this information publicly known and accessible, rather than keeping it exclusive to certain institutions. As previous studies on social security and privacy have shown, raising public awareness and promoting transparency are effective ways of mitigating potential risks, rather than allowing the information to remain confined to specific entities[111].

Methods

Dataset

Shazam

Shazam (https://www.shazam.com) is a popular music recognition service that uses audio fingerprinting technology to identify songs playing in a user's immediate surroundings. It works by recording a short audio sample (~ 5 seconds) using the device's microphone. If a match is found, the app returns the song's title, artist, and additional information like lyrics and video. Crucially, Shazam discoveries are distinct from typical streaming data, as they capture engagement with songs that are often (1) unfamiliar to the user and (2) curated by others in real-world environments, such as on the radio or in restaurants[54,55].

Beyond simple identification, users treat Shazam as a discovery tool—they can save identified songs, listen to a preview, share them, or stream full tracks on connected platforms like Apple Music and Spotify. This *active* engagement with unfamiliar songs makes Shazam a leading indicator of emerging trends. Songs frequently peak on the platform weeks before they do on radio or music charts[55], as intense Shazaming in a region can signal a song is catching on locally before it becomes a mainstream hit—a phenomenon known as the *Shazam effect*[112]. The platform's scale is substantial[113]: as of 2022, it served a global monthly user base of 225 million, processed 20 million daily identifications, and had achieved over 70 billion total discoveries. This makes Shazam a massive, real-world measure of active engagement with music.

Both Ukraine and Russia are significant markets for Shazam. Russia is one of Shazam's largest user bases globally. By 2015, Russia was Shazam's 4th largest country market in the world, installed by 35 million users and with about 8 million active users monthly in the country[114]. Shazam's penetration in Ukraine has been significant as well. While exact data are harder to find, by 2022, Shazam was considered one of the top music apps in Ukraine[115]. In particular, Shazam had around 0.39 million monthly Ukrainian users by 2022 (for comparison, Spotify had ~2.9 million monthly users and Apple Music ~0.42 million in the same analysis). Third-party mobile analytics (www.start.io) indicate that Shazam's user demographics is predominantly young and relatively male-skewed, although there is variation from country to country. For example, in the US, about 65% of Shazam users are male and 87% under 35 years of age; in Russia 56% are male and 87% under 35; and in Ukraine 54% are male and 76% under 35 (see Notes S1,2 for detailed descriptions on demographics of Shazam users).

Global Music Discovery dataset

We implemented a daily web crawler to collect the top 50 most-searched-for songs in Shazam across all available cities (N = 1,423) and countries (N = 53) for three years (Fig. 1). All data was obtained adhering to Shazam website's crawling limits and publicly available Terms and Conditions, which permit the use of publicly available data for non-commercial purposes (https://www.shazam.com/terms). During this time, the chart was updated frequently as our monitoring was able to capture changes happening at the day-to-day granularity. From this longitudinal collection, we created two datasets: The first, used for our main analysis, covers a six-month period centered on the invasion (26th November 2021 to 25th May 2022) and includes over 12.8 million music discovery events corresponding to 79,310 unique songs. The second, used for long-term trend validation (Fig. S1), spans two years and includes over 66.5 million events for 273,988 unique songs. Collectively, we call this the Global Music Discovery dataset. The dataset only uses aggregate data of the most popular songs identified in Shazam both at the city and country level (Data and code availability). None of the queries used in the data can be linked to any particular individual or reveal private information. We created a web page with interactive plots for analysis and data exploration and visualization (https://musicdiscover.net).

World regions

We categorized the world into seven regions based on the World Bank analytical grouping[116]. This classification includes economies at all income levels and may differ from common geographic usage or regions defined by other organizations. Given that our study focuses on understanding cultural shifts in the post-Soviet countries, we made a separate category for the post-Soviet region, which includes all countries from the former Soviet Union available in our dataset, namely, Ukraine, Russia, Belarus, and Kazakhstan. We refer to the “Europe & Central Asia” region only as “Europe”, as our dataset did not include any Central Asian countries. The categories of world regions defined in the study are visible as a world map in Fig. 1A. Table S6 outlines the classification of all 53 countries.

Comparison with other data sources

Spotify and YouTube Music

To examine the extent to which music discovery data from Shazam aligns with other major platforms, we compared its top 200 weekly charts with those from Spotify (top 200; https://spotify.com) and YouTube Music (top 100; https://charts.youtube.com). For this cross-platform analysis, song lyrics were scraped using grounded searches by Google’s Gemini 2.0 Flash model, and the language of the lyrics was detected using the same procedure as our main analysis (Sung language in Methods). Given Spotify and YouTube Music do not publish charts at the city-level, we conducted our comparison at the national level for the same six-month duration of our study (N overlapping countries: Shazam vs. Spotify = 48; Shazam vs. YouTube = 41; Spotify vs. YouTube = 54).

Our primary goal was to validate our main findings. This analysis confirmed the key national trends observed on Shazam (Fig. 2a) are not a platform-specific artifact. Both Spotify and YouTube Music data also reflected a rise of local Ukrainian songs in Ukraine and a decline of Russian music in both Ukraine and Russia, validating our main finding (Fig. 2b).

Next, to understand the unique characteristics of each platform, we quantified their content overlap. To account for potential minor spelling discrepancies in song titles and artist names across platforms, we used fuzzy string matching (via the *stringdist*[117] package in R). The matching algorithm generates a score between 0 and 1, with 0 indicating completely different strings and 1 indicating identical strings. We established a threshold of 0.70 to determine whether a match was considered successful, a threshold that has shown to be reliable in matching songs across different sources[118]. For each pair of platforms, we calculated the overlap proportion by determining the fraction of songs from the smaller chart that also appeared in the larger one (i.e., if platform A contains fewer songs overall, the overlap proportion equals the number of A's songs that also appear in platform B divided by A's total song count). The results showed a consistently modest overlap: Shazam vs. Spotify = 33.9%; Shazam vs. YouTube = 33.6%; and Spotify vs. YouTube = 32.8%.

The relatively low overlap in content may suggest that these platforms capture different, complementary stages of public music consumption—Shazam reflecting early discovery and Spotify/YouTube reflecting more established listening habits—and may also serve distinct user bases with different listening preferences and usage patterns. The fact that such trends of Figure 2 were observed independently across these distinct stages of engagement provides strong evidence for their significance. While technical factors like platform-specific copyright agreements may also contribute to the low overlap, the analysis suggests that our findings reflect a fundamental societal shift, not an artifact of a single platform.

Socio-cultural values

To examine the extent to which music discovery data from Shazam reflects shared cultural interests and values globally, we compared the pairwise music similarity across all countries using the Global Music Discovery dataset, with the pairwise similarity in socio-cultural values derived from the WVS data (World Values Survey in Methods). Music pairwise similarity was calculated using the Jaccard similarity coefficient (Discovery similarity in Methods). Socio-cultural similarity was calculated using the cosine similarity across all the questions on WVS. The locations where the survey was collected were first matched with the Shazam data by finding the minimum haversine distance between the two datasets. We then excluded all surveys that were conducted more than 100 km away from the nearest city included in the Shazam data. This resulted in a match of 508 cities, while the two similarity matrices revealed a strong correlation (two-tailed Pearson $r = 0.63$ [0.63, 0.63], $P < 0.001$).

This suggests that cross-cultural similarity in people's musical interests align with similarities in socio-cultural values.

Music content analysis

Sung language

We determined the language of songs' lyrics using *FastText*, a pre-trained word embedding machine learning model capable of identifying 176 languages[119]. We excluded 37.50% of songs which contained no lyrics. While this is a relatively large proportion, the number of missing lyrics across the post-Soviet countries were similar, ranging between 26.06% to 38.24%. We further excluded 8.98% of songs that resulted in a low confidence score in language identification (below 0.70 with full range from 0 to 1). The exclusion percentage below this confidence threshold per language used in the analysis of Fig. 2a were not substantial (English = 9.7%, Ukrainian = 3.0%, Russian = 0.5%, Kazakh = 1.2%).

We validated the language detection method in two ways. First, the author O.S., who is a native Ukrainian speaker and understands Russian, validated a random subsample of 100 songs each that were classified as Ukrainian and Russian that passed the confidence threshold of FastText. Validation results confirmed that all except one ambiguous case (a song with a mix of both Ukrainian and Russian that was classified as Ukrainian) were correct. Second, we prompted a large language model (LLM) GPT4o with the full lyrics to identify the language across all 1,178 unique songs that appeared among the post-Soviet countries (see Note S4 for prompt instructions), and compared this with classification of FastText. The two methods demonstrated high agreement, matching in 98.4% of cases. Notably, for songs identified as Ukrainian by either method, we observed 100% agreement between FastText and GPT-4o. For Russian-language songs, the agreement was slightly lower but still remarkably high at 99.4%. These validation results indicate that our language detection approach is highly accurate.

A song was considered "local music" if the language of its lyrics matched the country of discovery (e.g., a song in the Ukrainian language discovered in Ukraine). We calculated the proportion of songs in the most frequent languages across the post-Soviet countries (Ukrainian, Russian, Kazakh, and English) by bootstrapping songs across the days, with effect sizes of change computed comparing pre- and post-invasion periods (Fig. 2; Statistical analysis in Methods).

Trend validation

We tested the robustness of our results in several control analyses (Fig. 2; Sung language in Methods). First, we tested the stability of our results over a longer time window of two years, from November 2021 to December 2023 (Fig. S1). Specifically, we tested the extent to which the trends of songs' language observed for six months in our study window persisted. For each country, we computed the first day in which the proportion of Ukrainian or Russian songs returned to their pre-invasion baselines (defined as the mean proportion of the entire pre-invasion period). The results revealed that the cultural shifts observed in Ukraine (increase in local music and decrease in Russian music) persisted over the next year: Ukrainian music consistently remained above 11.24% [9.55, 12.54], while Russian music did not exceed 38.82% [36.69, 41.63]. In contrast, the cultural shifts observed in Russia, Kazakhstan, and Belarus (decrease in Russian music) returned to their baseline levels within a year (see Fig. S1 for long-term trends). Specifically, it took 208 [207, 211] days after the invasion for Russia, 117 [41, 217] days for Belarus, and 89 [85, 116] days for Kazakhstan.

Second, we tested for potential seasonal effects, as particular months in the year (e.g., holiday seasons, christmas) can link to different consumption patterns[19,29]. We compared the trends in our study with the same months in the following year by computing Pearson correlations between the two trends (Fig. S2a). Across the four post-Soviet countries, we found no evidence showing the same trends in the same months of the following year (correlations were either small and non-significant, $P > 0.05$, or negatively correlated), ruling out the possibility that our results are explained by seasonal patterns. Finally, we examined the relative magnitude of the effects we observed in the study period against the fluctuation in trends that happens over time (Fig. S2b). Excluding the study period months, we randomly sampled the same six months period window across the entire longitudinal data using 1,000 bootstraps (Statistical analysis in Methods). We split each of these samples in half and compared the changes by the effect size, resulting in a distribution of potential trends. We then examined how our observed effect falls in this distribution. Our results showed that the trends in Ukraine and Belarus were significantly above chance ($Ps < 0.001$), falling outside the expected values accounted for by random fluctuations. The results observed in Russia (P = 0.44) and Kazakhstan (P = 0.10) were in the expected direction to the norm, but not statistically significant.

Word embedding

We used pre-trained word embeddings available from Open AI (www.openai.com, model *text-embedding-ada-002*, data collected in December 2023) to extract semantic vectors of the songs based on lyrics. This embedding forms the bases for the Large Language Models (LLMs) developed by the company and used in their application GPT. For each song that was discovered in Ukraine and Russia where lyrics are available (N = 2,826), we used the API query to extract the word embedding feature vectors of the lyrics, consisting of 1,536 dimensions. The non-English lyrics were first translated into English using Open AI's GPT4o (see Note S4 for prompt instructions). The translation was crucial as we want to compare relations between all lyrics focusing on the semantic context and meaning (not differences in the languages themselves).

Keywords

To identify the keywords that stem from Ukrainian and Russian songs pre- and post-invasion, we computed the log-odd ratio approach described by Monroe et al.[120]. This approach is similar to term frequency–inverse document frequency (TF-IDF), a widely used approach in Natural Language Processing to identify important words across documents[121]. Each word was assigned a zeta-score that indicates the importance of the word in the group (i.e., pre- versus post-invasion songs). We then cleaned and processed (e.g., lemmatization) the words in the lyrics with custom stopwords to remove interjections such as "ooh" and "yeah" (based on two author agreements). Next, we extracted the 30 top zeta ranked keywords from the Ukrainian and Russian lyric songs, separately for pre- and post-invasion as word cloud visualizations using the *ggwordcloud* package in R. The resulting word cloud in Figure 3b was carried out using lyrics translated into English (Word embedding in Methods), however, word clouds in original languages can be also found in Figs. S3.

War-related songs

We used a data-driven approach to identify war-related words based on the same word embedding extraction method described above (Word embedding in Methods). We applied a tokenized dictionary of all words (instead of entire lyrics) across songs discovered in both

Ukraine and Russia to identify war-related songs. Using the seed word “war,” we computed the cosine similarity across the embedding vectors of all tokenized words to find the closest neighboring words. This approach is analogous to previous studies relying on language models to assess semantic similarity[122,123]. Songs were then classified as war-related if their lyrics contained any of the top five war-related words—“war,” “weapon,” “armed,” “fight,” and “win.” We then calculated the daily proportion of songs that contained any one of these words in Ukraine and Russia, bootstrapping over songs per day (Statistical analysis in Methods). We found similar results when varying the number of war-related words, including only the inclusion of the word “war,” the top three and the top seven neighboring words (Fig. S3c).

Acoustic features

We used the Essentia library[124] (version *2.1-beta6-dev*) to extract low- and mid-level acoustic features of the songs discovered in Ukraine and Russia by using all available preview audio links for download and audio extraction (N = 2,222). Following standard practices in the music information retrieval literature[125,126], we included acoustic features that captured different aspects of music, ranging from timbre and rhythm to musical chords. Specifically, we computed the RMS loudness, dynamic complexity, spectral complexity, spectral centroid, spectral energy, zero-crossing-rate, beats per minute (bpm), chord change rate, mode (major or minor), and 12 bins of MFCC values. We used the low- and mid-level features as acoustic vectors for distribution comparison and visualization (see Fig. S4 for UMAP). We further compared each feature independently for pre- and post-invasion local songs in Ukrainian and Russian by computing the change in normalized z-scores (post mean - pre mean; Fig. 3d). All values were derived from 1,000 bootstraps across the songs (Statistical analysis in Methods).

Comparing distributions

We used UMAP for reducing the high dimensional vectors of semantic and acoustic features, using the *uwot*[127] package in R. Cosine similarity was used as a measure of distance, taking ten neighbors, which gave a good balance between the local and global structure (minimum distance = 0.1; number of epochs = 500). The proximity between two songs in the semantic space corresponds to the extent of shared semantic content (e.g., songs that talk about love or friendship), while proximity in acoustic space corresponds to similar musical styles as measured by their acoustic characteristics (e.g., songs that have similar timbre, rhythm, or music genre).

To identify high density areas of local music, we overlaid Kernel Density Estimations (KDE) on the UMAPs of Ukraine and Russia for pre- and post-invasion songs separately. We used the *MASS*[128] package in R to compute each density map with a grid size of 512 by 512. We then computed kernel smoothing with a Gaussian kernel with width selected by their best-practice heuristic with default parameters implemented in the package.

To measure differences between distributions of songs (*P* and *Q*) in the semantic and acoustic spaces between pre- and post-invasion songs, we computed the Jensen–Shannon Divergence (JSD) using the *philentropy*[129] package in R, written as:

$$JSD(P,Q) = \frac{1}{2}D(P,M) + \frac{1}{2}D(Q,M) \quad (1)$$

where *M* is defined as:

$$M = \frac{1}{2}(P+Q) \quad (2)$$

and *D(P,Q)* is defined as:

$$D(P,Q) = \int p(x)\log_2\left(\frac{p(x)}{q(x)}\right)dx \quad (3)$$

Note that the JSD is symmetric and results in a value between 0 and 1. When the two distributions are identical, the JSD is 0, while 1 when they are completely non-overlapping. Since JSD does not have a value below 0, we created a random baseline for reference by shuffling the pre- and post-labels. We then computed bootstrap estimates over the songs by taking the difference between true JSD and the random baseline as the estimate, where values near 0 indicate support for the null hypothesis (Statistical analysis in Methods).

Within-country analysis

City trends

We used our city-level data to study subnational variations within Ukraine and Russia, using language of the lyrics as a proxy for local music (Sung language in Methods).

To examine changes at the geographical level (Fig. 4a), we created a geographical raster map by using a kernel smoothing technique to interpolate geospatial data across a predefined grid of city locations. This method estimates values across the entire grid based on the spatial distribution of the observed data points. The geographical map was represented as a grid of cells, each defined by longitude and latitude coordinates. For visualization, we divided the cities into four quantiles based on their proportion of local music change from pre- to post-invasion. The quantile splits accounted for the skewness in the distribution of data points and ensured consistent mapping across all our geographical visualizations. Kernel smoothing was applied as follows:

$$G_D(x) = \exp\left(-\frac{x}{D}\right) \quad (4)$$

where *x* represents the distance between a grid cell and a data point, *D* is a distance parameter determining the smoothing extent. This function ensured that closer points had a higher influence on the interpolated value at a given grid cell, with the influence decreasing exponentially with distance. The interpolation across the grid was achieved through the following process: (1) for each cell in the grid, distances to all data points were calculated, and corresponding weights were derived using the smoothing function; (2) these weights were then normalized so that the overall weights sum to one; (3) the interpolated value for each cell was obtained by computing the weighted sum of the values of all points, with weights reflecting the spatial relationship between the cell and the points based on the defined smoothing function. The distance parameter *D* was set based on the mean distance between all pairs of data points divided by 10 to obtain sufficient spatial resolution.

To examine temporal trends (Fig. 3c), we calculated the proportion of local music per city within Ukraine and Russia for each day, bootstrapping over the songs and by fitting a GAM over the bootstrapped means (Statistical analysis in Methods).

World Values Survey

To examine the associations between city-level variations in change in local music and pre-existing socio-cultural values within Ukraine and Russia, we used the World Values Survey (WVS) data collected from 2017 to 2022, which covers 64 countries (*Wave 7*)[130]. WVS is a longitudinal global research project that includes more than 300 questions to measure people's social, political, economic, religious, and cultural values.

A total of 1,289 survey responses across 351 unique geolocations were available from Ukraine, and 1,796 responses across 189 geolocations from Russia. After excluding 58 questions that had no responses both in Ukraine and Russia, there were 318 questions remaining. To reduce noise, the geolocations were re-grouped by a single decimal granularity of latitude and longitude geocoordinates. Survey response values corresponding to 0 were treated as missing and were replaced by the mean value of their higher-level geographical boundary (i.e., iso 3166-2 corresponding to municipalities, see https://www.iso.org/standard/72483.html). To account for different units and response types, all questions were standardized with z-scores.

To reduce the dimensionality of the questions into fewer meaningful factors, we performed a Principal Component Analysis (PCA) including all data available in the two countries, using the base function *prcomp* in base R. We found that the three first latent dimensions explained 20.69% of the variance (see Table S3 for the top 10 loadings and related questions for each dimension). The first dimension (accounting for 7.70%) captured variability in socio-cultural values related to ethical and moral judgements, measuring the extent to which individuals are against unethical actions and behaviors (e.g., stealing property, terrorism, violence, domestic abuse). The second dimension (accounting for 6.90%) captured low institutional trust, including institutions such as the government, the police, and the justice system. The third dimension (accounting for 6.09%) captured religiosity and trust in international institutions, including importance of religion, belief in heaven, and trust in major international institutions (e.g., the European Union, NATO, and the United Nations). Both in Ukraine and Russia, the loadings of PCA 3 (Fig. 4b) were significantly associated with changes in local music discovery post-invasion (Ps < 0.001). The results using PCA 1 and PCA 2 only revealed a significant correlation with PCA 1 in Ukraine ($P < 0.01$), while the other associates were non-significant (see Fig. S5; see Note S3 for comparison with cultural dimensions by Inglehart–Welzel). We used the same smoothing technique described above (City trends in Methods) to visualize the PCA loadings of each city as a raster map.

Census analysis

We replicated our findings of Fig. 4b using census data on ethnic and linguistic proportions in Ukraine, and only ethnic data in Russia due to the lack of available linguistic data (Fig.

S7). For Ukraine, we used the 2001 Census. This is the first (and the last, making it most recent) national census conducted in Ukraine since it gained independence from the Soviet Union in 1991, carried out by the State Statistics Committee of Ukraine (https://stat.gov.ua). There are many debates surrounding the validity of the 2001 census[131,132], and considering it is two decades old, any interpretation needs to be taken with caution. For Russia, we used the most recent 2021 Census, carried out by the Russian Federal Government (https://eng.rosstat.gov.ru). The results of census analysis were similar for Ukraine but did not reach significance for Russia (see Fig. S7 for further statistics).

Google trends

To examine whether the within-country variations observed in Figure 4 can generalize beyond Shazam, we acquired additional data from Google Trends. Focusing on Ukraine, we used the top 10 songs in Ukrainian language (see Table S1 for details of the songs) as queries to gather data on the search interest over time across all available 26 regions within Ukraine from Google Trends. The query was made separately for the song *title* and *artist*, as combined searches were too rare to provide reliable volume data. We then aggregated the outputs to compute the mean search interest for each day and per region. This Google Trends analysis not only confirmed the overall post-invasion surge in Ukrainian songs, but also mirrored the exact regional divisions within Ukraine we identified in Figure 4, with a strong correlation with the WVS data (Fig. S6).

Discovery similarity

To examine temporal trends in the similarity of song consumption within each world region (i.e., their shared repertoire), we developed a daily measure of regional song discovery similarity. Our analysis utilized the complete set of unique songs discovered daily in each country, rather than predefined charts. For each day within a given world region, we first calculated the Jaccard similarity coefficient, $J(A,B) = |A \cap B| / |A \cup B|$, for every possible pair of countries based on their unique song sets. The region's final daily similarity score was then computed as the average of all these pairwise indices. Single-country regions (South Asia, South Africa) were excluded as no pairwise comparisons could be made. Note that similar measures of shared cultural consumption have been found to reflect cultural proximities that change along economic, social, and geopolitical dimensions[65,66].

To model trends and estimate uncertainty, we employed a bootstrap procedure. For each day, we generated 1,000 bootstrap samples by resampling (with replacement) the set of that day's pairwise Jaccard indices and recalculating the regional average for each sample. This process resulted in 1,000 complete time series of regional similarity. We then fitted a separate Generalized Additive Model (GAM)[133] to each of these 1,000 time series (Statistical analysis in Methods). The final trend lines and confidence intervals shown in our figures were derived by averaging the results of these models.

Because different regions exhibit vastly different baseline levels of internal song similarity, for visualization purposes (Fig. 5a), the daily mean similarity scores for each region were normalized using z-scores to account for different baseline levels of similarity. However, note that all reported statistics were computed on the raw, non-normalized data. We excluded a single day of data as an outlier (z-score > |2|) to control for potential data artefacts and technical issues on Shazam, a step that did not influence the reported GAM results. Finally, the overall magnitude of change between the pre- and post-invasion periods was measured using bootstrapped Cohen's d effect sizes (Fig. 5b; Statistical analysis in Methods).

Network analysis

Network inference

Using the Global Music Discovery dataset, we compiled the diffusion cascades of all unique songs (N = 79,310). A song cascade describes the spatiotemporal trajectory of a song as it is discovered extensively across cities over time (see https://musicdiscover.net for interactive visualization of cascades for selection of songs). To infer the likely directional pathways of diffusion from these cascades, we used the NETINF algorithm[67], a generative probabilistic model that has been extensively used to reconstruct the underlying diffusion networks for other online media, such as social media, blogs, and news articles. Given only the times when cities adopt new songs, the algorithm reconstructs the connectivity of the underlying network by maximizing the likelihood of the observed cascades under the probabilistic model. Specifically, the model infers a directed edge (*A*, *B*) in the network if city *B* tends to adopt new song trends soon after city *A* across multiple cascades. We configured the algorithm using its default setting for the exponential model parameter (alpha

= 1) and set the number of internal optimization iterations to 10,000 per run. This number of iterations was determined to be sufficient for model convergence based on preliminary analyses while remaining computationally tractable.

We observed significant variation in the number of unique songs appeared on the daily top discovery chart across different cities (Fig. S12a). To prevent cities with larger unique song volumes from disproportionately influencing the network structure and to ensure a robust estimation, we employed a bootstrapping procedure. Specifically, we ran the model 1,000 times. In each iteration, we sampled a balanced set of 100 unique songs from each city's daily discovery pool (Statistical analysis in Methods). This balancing ensures each city contributes equally to the network inference within each bootstrap run. A split-half correlation analysis suggested that after 100 bootstrap iterations, it is sufficient to obtain a reliable estimate of the network (see Fig. S12b for network reliability analysis).

The final network was constructed by aggregating the results across these 1,000 bootstrapped networks into a single weighted network by summing all unique edges. We used the frequency of edges between two nodes as a measure of edge strength (or weights), which reflects the degree of shared musical interests (i.e., similar music discovery trends). Edge strength ranges from 0 (edge was never inferred in any of the bootstrap datasets) to 1,000 (edge was always inferred). When visualizing the resulting network (Network visualization in Methods), we reduced the density of the inferred networks by removing weak edges that occurred less than 5% of the time. We found this threshold to provide a good tradeoff between removing noisy edges with little structural importance, at the same time, maintaining meaningful structures of the networks both globally and locally.

Network validation

To test the robustness of the NETINF algorithm, we repeated the network analysis in the post-Soviet region (Figs. 5c,d insets) using a simpler method based on the co-occurrences of songs between cities. This is analogous to the approach of measuring discovery similarity (Discovery similarity in Methods), where we computed the overlap of songs between all pairs of 100 post-Soviet cities in the Global Music Discovery dataset. We then compared the weights of the edges in the networks obtained using this method and the NETINF algorithm, which indicated a significant degree of overlap between the adjacency matrices for both pre- (two-tailed Pearson $r = 0.49$ [0.48, 0.51], $P < 0.001$) and post-invasion ($r = 0.56$

[0.55, 0.58], $P < 0.001$) networks, validating the robustness of the NETINF algorithm. We chose to use the network inference approach in the main study as it is able to account for temporal trends of songs and infer directional pathways of influence. Additionally, we visualized the co-occurrence network for comparison (Fig. S10). We reduced the density of the network by applying a backbone algorithm[134] to the city-by-city matrix, obtaining only the edges that were statistically significant using the disparity filter in the backbone[135] package in R. We balanced the resulting number of edges in the pre- (N edges = 1,014) and post-invasion (N edges = 966) networks by adjusting the alpha level to 0.285 and 0.230 respectively.

Network visualization

We performed several steps to ensure an alignment of layouts of the pre- and post-invasion networks for visual comparisons. First, we created two city-by-city matrices to represent the inferred networks of pre- and post-invasion. The matrices ($A_{i,j}$) contained all possible pairwise comparisons across the 1,423 cities, using the inferred edge strength (Network inference in Methods) ranging from 0 (edge is absent) to 1,000 (maximum possible edge strength). Second, we joined the original matrices with their transposed versions to form a new joint matrix, written as:

$$C = \begin{bmatrix} A & A' \\ B & B' \end{bmatrix} \quad (5)$$

where A and B are the original matrices, and A' and B' are their matrix transpositions ($A'_{i,j} = A_{j,i}$). The transposition step ensures that both incoming and outgoing edges are taken into equal account. Finally, to get a normalized similarity matrix, we computed the correlations, where C is n x p matrix, then the correlation $D[i,j]$ is calculated as:

$$\frac{cov(C[:,i], C[:,j])}{std(C[:,i]) \times std(C[:,j])} \quad (6)$$

The last two steps (equations 5 and6) ensure that the pre- and post-invasion matrices are distributed within the same shared visualization space.

Our method offers a considerable advantage over previous visualization methods that perform dimensionality reduction independently, and then attempt to align networks *a posteriori*[136,137]. We used Gephi (https://gephi.org) for the final visualization of the networks, an open-source visualization software for graphs and networks. The layout was determined using the *Yifan Hu Proportional* method[138] (optimal distance = 120, relative strength = 0.20, convergence ratio = 0.0001). We first obtained the joint visualization using both pre- and post-networks and then separated them to display them as independent subplots (Fig. 5c,d).

Network similarity and change

We compared the similarity between pre- and post-invasion networks at a global scale by computing bootstrapped split-half Pearson correlation between the city-by-city pairwise matrices obtained through the NETINF algorithm (Network inference in Methods; see Fig. S8 for heatmaps). We computed the amount of change in the networks by measuring the percentage change in the number of edges in the pre- (N_{pre}) and post-invasion (N_{post}) networks, written as:

$$\text{Percentage of change} = \frac{(N_{\text{post}} - N_{\text{pre}})}{N_{\text{pre}}} \times 100 \qquad (7)$$

This procedure was performed separately for each NETINF inference bootstrap datasets and aggregated to provide the mean and confidence estimates (Statistical analysis in Methods). Using the formula, we examined the changes within each world region (Fig. S9).

Ukraine, Russia, and Europe

For each city in Ukraine and Russia, we computed the number of new edges formed with cities in Europe, including both incoming edges (from Europe) and outgoing edges (to Europe; Fig. 5e). To explore which cities in Europe developed new edges with the post-Soviet region, we created a geographical map visualization (Fig. 5f) indicating any city in Europe with at least one new edge formed in the post-invasion network (i.e., edge that did not exist in the pre-invasion network).

Statistical analysis

Unless stated otherwise, all bootstrap analyses were performed with 1,000 datasets with replications to derive the mean. Confidence estimates were derived from the 2.5% and

97.5% quantiles of the bootstrap means. For a statistical test comparing two conditions, we determined statistical significance at alpha level of 0.05 using non-parametric tests. Pearson and Spearman correlations were adjusted for multiple comparisons using Bonferroni method. Pearson correlation is reported throughout, with an exception of analysis on within-country variation (Within-country analysis in Methods) where Spearman correlation was used due to the skewness of the data. Cohen's d was used for effect size estimates with signs to indicate the direction of effect[139]. Data analysis was conducted using R (version *4.4.0)*. All analysis scripts are available for transparency and reproducibility (Data and code availability).

Data and code availability

All data supporting the findings of this study are available as an OSF repository at https://osf.io/ra38k. We also include a web page with an interactive version of the main figures at https://musicdiscover.net. All analysis code supporting this paper is available at https://github.com/harin-git/mus-war.

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Supplementary information

Supplementary information has been submitted along with the manuscript. It can also be viewed by following the link: https://osf.io/ebrgw.

Authors' contributions

Conceptualization, investigation, administration, methodology, analysis, interpretation, and writing: H.L., M.A., M.P., and N.J. Initial conception of the idea: M.S., O.S., H.L., and M.A. Data collection and curation: H.L. Interactive plots: P.R. Data interpretation: O.S. and M.S. Project supervision: O.T., M.P., and N.J. All authors worked collaboratively to discuss methods, analysis, and writing throughout the process of preparing the published work.