Can AI Transform Music Production? – Intervention Analysis for Short Time Series on the Global Supply of Music Recordings.

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The introduction of artificial intelligence (AI) technology to the public has sparked a widespread debate regarding its implications for the economy and society, including the cultural and creative industries, within which music. While the debate often focuses on AI's potential to automate certain parts of creative labor or the potential of AI to become a creator itself, empirical evidence about the real-world impact in the music industry remains scarce.

This thesis addresses a critical gap in the literature by analyzing how the advent of generative AI tools has affected the global supply of music recordings.
The study applies an intervention analysis framework, similar to the methodological approach by Handke (2012) for digital copying, conceptualizing it as a natural experiment.

Using global release data from the MusicBrainz database, the thesis covers the years from 2000 to 2025 and tests whether the supply of new music underwent a significant structural change after 2016, which is a period identified as the first year in which music AI production programs were introduced, the beginning of a widespread AI adoption in music creation.

To assess the effect of AI on the global supply of music recordings, the analysis applies the C statistic, first developed by Young (1941) and applied by Tryon (1982). Linear regression and first differencing are used to remove any deterministic patterns from the pre-AI period (2000-2015) in order to correctly assess the C statistic. The Z statistic derived from the C statistic and applied to the full time series (2000-2024) reveals statistically significant structural change for the period after the introduction of AI, which indicates that AI introduction coincides with a disruption in supply dynamics.

Further analysis at the genre level is conducted between technology-dependent genres (pop, dance, techno) and traditionally acoustic genres (jazz, classical). The results of the genre-specific analysis show that all genres experienced statistically significant change; the effect was most pronounced in pop and jazz genres, rejecting the alternative hypothesis that AI integration impacts pop, dance, and techno genres more than jazz and classical.

Overall, the findings suggest that the introduction of AI into music production has not only sustained the existing growth trends but also altered the underlying structure of the supply of music recordings. The results contribute to the field of cultural economics by providing empirical evidence of how digital technologies might possibly have a significant impact on the supply of music recordings and a music sector overall. Researchers are invited to expand this work by exploring the potential for the transformative ways that AI may bring to the cultural and creative sectors in Europe and globally.

KEYWORDS: AI, music industry, supply, productivity, intervention analysis

Word count: 10,800

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1. Introduction

The first quarter of the twenty-first century witnessed what could possibly be called a transformation of the cultural and creative industries, especially while focusing on the sector that will be under evaluation in this paper - music. It changed the ways in which cultural products are produced and consumed. The music industry went through a rapid digitalization process, transitioning from CDs to music streaming as the primary revenue source by 2024 (IFPI, 2025). The latest technological advancement, generative artificial intelligence (AI), appears as a possible disruptor in a long and eventful process of music industry digitalization. Recently, generative AI technologies received broad attention for their potential and have been used commercially in various sectors (Drott, 2020; Li, 2025). However, most empirical studies conducted so far have been primarily concerned with consumer behavior (Henry et al., 2024; Tigre Moura & Maw, 2021) or have examined productivity implications outside of creative industries (Cui et al., 2025; Hoffmann et al., 2024; Raj & Seamans, 2018). The first generative AI music production programs were introduced in 2016 (e.g. Magenta, AIVA). Hence, scientific research addressing the consequences on the industry had not been tackled, accounting for a short time span that a possible impact would consider. This situation reveals a clear gap in the understanding of AI's effect on the supply side of music production.

In recent years there has been more engagement from music industry professionals regarding AI, which indicates the need for a thorough understanding of the potential that this technology might have and possible threats that it poses (European Parliament, 2025; European Writers Council, 2025; Robins-Early, 2024). Concerns around AI include the legal uncertainties regarding copyright law and insufficient transparency about the content that AI companies use for training purposes (European Writers Council, 2025). Furthermore, the availability of AI music production software and AI music creation technologies at a lower cost and with faster processes through automation raises concerns about the displacement of human producers and job losses (CISAC, 2024).

This, in turn, puts pressure on the policymakers within European and global contexts to act on behalf of the industry professionals (Culture Action Europe, 2024; Maroutsis, 2024; Society of Audiovisual Authors, 2024).

This thesis addresses a specific research gap by conducting a quantitative analysis of the effects of generative AI technologies on new music releases globally from their introduction to the music production programs in 2016 and analyzes their impact across specific music genres - pop, dance, techno, classical, and jazz. The genre-specific approach accounts for possible differences in supply between genres heavily dependent on technological production tools (pop, dance, techno) and those traditionally employing acoustic instruments as the main component in recordings (classical, jazz).

The central hypothesis (H_1) tested in this paper is whether the introduction of generative artificial intelligence in 2016 shows a statistically significant shift in the global supply of music recordings. The second hypothesis (H_2) tests whether the shift was statistically significant for genres intrinsically dependent on technological production tools (pop, dance, techno) in opposition to more traditionally acoustic genres (classical, jazz).

To adapt the analysis to data restrictions, the paper uses an intervention analysis for short time series that was developed by Young (1941) and adopts a methodological approach similar to that of Handke (2012). The chosen method serves as an initial approach to evaluate whether sudden changes, like the introduction of AI, could significantly influence the dependent variable, particularly valuable when limited data restricts the use of conventional time series or panel data methods.

The results show evidence that the introduction of AI music production tools, first published in 2016 has significantly increased the global supply of new music recordings, although it is noted that the general trend was already upward prior to the introduction of AI. Genre analysis suggests that the AI's impact on genres varies, with pop and jazz genres showing the most substantial effects and all genres showing statistically significant results nevertheless.

The findings of this paper highlight important policy implications, namely the need for transparency about AI-generated and AI-assisted music-making and potential copyright concerns. Moreover, research has previously shown that due to digitalization, the growing number of new music recordings, contrary to the earlier belief in the democratization of music production, remains highly concentrated at the top (Resnikoff, 2016). This suggests that a further abrupt growth in music supply might only exacerbate the problem.

This thesis contributes to ongoing academic debates by empirically evaluating AI's transformative potential in the music industry, underlining its societal implications. Using global release data from the MusicBrainz database, the thesis covers the years from 2000 to 2024 and tests whether the supply of new music underwent a significant structural change after 2016, which is a period identified as the first year in which AI programs for music production were introduced, marking the beginning of widespread AI adoption in music creation. The study shows the importance of further research, especially considering the evolving nature of AI technologies. Researchers are encouraged to explore AI tools' impact more in depth and using more comprehensive datasets. It is also advised to consider aspects such as country-specific data or detailed genre analysis.

The paper continues as follows: Chapter 2 outlines the literature on AI, productivity, and digitalization. Chapter 3 describes the data and methodology used to analyze the number of new releases in the sound recording market. Chapter 4 presents the analysis and results. Chapter 5 discusses the implications of results, and Chapter 6 shows the conclusions.

2. Theoretical Framework

2.1 AI and productivity

New technologies allowed many processes to become more efficient, faster, cheaper, and easier. Among these, artificial intelligence has experienced especially rapid development. Although AI was first developed in the twentieth century, it was particularly after 2022 with the introduction of large language models (LLMs), such as ChatGPT, Gemini, and LlaMA, that the technology gained widespread public accessibility. These models, trained on vast datasets, significantly expanded the capabilities and reach of AI to a broader audience, making the technology more accessible.

Currently, research increasingly explores AI's impact on innovation, product design, and productivity at the firm and individual levels (Brynjolfsson et al., 2023; Dohmke et al., 2023; Noy & Zhang, 2023; Pan et al., 2017; Peng et al., 2023). Generative AI, although still developing, is progressively reaching all sectors of the economy (Acemoglu et al., 2022), including the cultural and creative industries (Amankwah-Amoah et al., 2024).

It has been a long-standing concern that the technological innovation, together with its productivity enhancement for the sector, may lead to widespread unemployment. Despite the fears, the last two centuries of technological advancement and increasing automation have not led to job losses generally (Autor, 2015). However, the accelerating capabilities of artificial intelligence renewed fears about a possibility of replacing human labor on a scale that was not seen before, known as "automation anxiety" (Akst, 2013), a term that well captures the societal unease surrounding rapid technological change, with ever-fast developing new models of AI. These concerns remain valid today, particularly as companies such as Duolingo and Klarna increasingly let go of their human employees to integrate AI into their core operations (Hari, 2025; Peters, 2025).

The recent development of generative AI in cultural and creative industries shows that many parts of cultural labor may now be subject to automation. While Bekar (2013) claims that the creation act remains inherently human, his position is increasingly challenged by recent advancements in technology. Moreover, some activities will always experience productivity gains faster than others, for example, manufacturing. In the arts, such as music, a major challenge in pursuing productivity gains is reducing the time and effort required to create a product without compromising its quality.

Another concern raised regarding productivity is the question of whether those developments can be a substitution for human labor or its complementation. In this regard, the differentiation between the sector overall and the individual workers requires a sectoral and individual-level analysis. As Akst (2013) notes, “ automation makes us better off collectively by making some of us worse off.”

In the case of AI, the implications for cultural workers extend beyond job displacement. Most publicly available AI tools rely on large-scale training data taken from existing human-created content (Potter Clarkson LLP, n.d.). For instance, an AI capable of composing or mixing music must first be trained on pre-existing musical works, which raises significant legal and ethical questions regarding intellectual property (IP), a foundational role in the music industry, protecting the rights of artists, and ensuring fair compensation. These issues remind of the disruptions that music industry occurred in the first decade of the 21st century during the “Napster era”, when the unauthorized distribution of music fundamentally altered the industry landscape. Today, similar concerns emerge as AI systems are trained on copyrighted data. It is a topic brought to discussion with EU officials by artists’ organizations with connections to the AI Act in the European context. Artists’ unions advocate for transparency and assessment of the legal framework for copyright in the context of European law (Culture Action Europe, 2024; Maroutsis, 2024; Society of Audiovisual Authors, 2024).

Recent research in this matter shows that, with an example of AI in the visual sector, AI may substantially enhance human creative productivity by 25%, as well as raise the value of the artworks by 50% (Zhou & Lee, 2024). While Zhou and Lee (2024) show significant productivity gains, their analysis largely ignores questions of artistic authorship and audience reception, which are the key concerns in evaluating cultural labor.

However, using AI may reduce content novelty. Commercial applications, such as music for advertising, games, or film, may prioritize efficiency over uniqueness and therefore benefit from AI integration. In contrast, fields such as songwriting or indie music, which strongly rely on emotional authenticity, may be less compatible with automated production methods.

AI's technical capabilities are advancing to the point where roles such as sound engineering may become automated. AI can perform tasks like mixing and mastering at a level comparable to or exceeding human capabilities. However, whether artists and producers will accept these changes remains unknown, since technological efficiency is not necessarily equivalent to artistic satisfaction. In times greatly dominated by digital tools, the interpersonal aspects of collaborative music production may continue to hold intrinsic value, even if seemingly economically inefficient.

Artificial intelligence has the potential to change and possibly grossly enhance the productivity of the creative sectors, particularly music. Alongside increased efficiency and reduced production costs, there are concerns regarding job displacement and the lack of artistic originality. The contemporary debates mirror those from the early 2000s regarding unauthorized digital copying. Although the common fear that the supply of original works and the quality of it will reduce proved to be exaggerated (Handke, 2012; Landes, 2002), the music industry is still facing the consequences of structural changes.

In conclusion, although the ongoing process of technological innovation brings hopes and opportunities for more labor efficiency and automation, it does show that the “automation anxiety” is not without merit. Ultimately, even if collective productivity improves, these gains must be weighed against their impact on individual workers in cultural and creative sectors, such as music.

2.2 Digitalization

Digitalization has brought substantial changes to the creative sector, beginning with the unauthorized copying of music recordings and later transforming the way music is accessed through streaming platforms. These platforms have not only altered consumer listening habits when shifting from albums to playlists but have also become the primary means of releasing new music. Moreover, streaming has enabled deeper insight into listener preferences, reshaping music marketing and distribution models.

The introduction of generative AI into creative industries may prove similarly disruptive (Amankwah-Amoah et al., 2024). However, only in recent years have technological advancements allowed for broader AI application in the cultural sector. Digital distribution channels have diversified the ways in which music is consumed and contributed to the emergence of the "long tail" in music business. Moreover, digital platforms enabled a broader variety of music to be offered online at a lower cost, making use of technologies such as algorithmic personalization to present customized content to their users (Strachan, 2013).

On the demand side, the shift from physical formats to streaming and downloading has further expanded music consumption (Rechardt, 2025). On the supply side, the production of digital music has become increasingly affordable. The decline in both marginal and fixed production costs facilitated by home studios, cloud storage, and software tools has lowered the entry barriers for independent musicians (Kretschmer et al., 2001; Varian, 2005). This decrease in costs has allowed artists with limited exposure to enter the market more easily.

Digital platforms also benefit from informational externalities. On one hand, user-generated content such as reviews and recommendations can enhance consumer awareness and stimulate demand. On the other hand, platforms act as intermediaries, leveraging indirect positive externalities between different sides of the market. Models like "freemium", in which users access music for free while advertisements finance the service, indicate how multi-sided markets reshape value creation.

2.3 The long-tail theory

The long-tail effect, described by Anderson (2006), underlined the potential for a change that might come with the digitization process for the supply side of the music industry. The theory introduced by Anderson (2006) says that the decline of CDs toward digital music led to a growth in lesser-known, niche music products that did not become mainstream hits. However, by the combined demand for the non-hits, new valuable subcultures emerged around pop-rock genres. This, in turn, contributed to making cultural goods more widely accessible and inclusive (Anderson, 2006). The long tail means that the potential aggregate demand from the marginal markets in pop-rock music that individually were not profitable in the traditional market can, with online distribution, compete with the better-known artists. Successfully applying this strategy, firms can realize significant profits from selling small volumes of hard-to-find items to many customers instead of only selling large volumes of a reduced number of popular items. The total sales of this large number of “non-hit items” correspond to the long tail (Coelho & Mendes, 2019).

The development of more affordable production tools, such as Ableton (est. 1999) or Logic Pro (est. 1993) allowed musicians to manage their entire production process independently. Moreover, the founding of internet platforms such as YouTube or MySpace allowed beginner musicians to showcase their work for free without gatekeepers, such as labels or critics. These developments have fostered hopes of democratizing the music industry, reducing reliance on traditional promotional channels like television and radio, and increasing visibility for emerging artists. Bounie et al. (2010) find that the best-selling digital products differ from those in physical stores, indicating a less concentrated demand structure in online environments. Despite this, the long-tail theory has not entirely displaced the superstar phenomenon.

2.4 The superstar theory

The superstar theory of Rosen (1981) explored how the small differences in talent lead to outsized differences in earnings, and the availability of the new technology fosters the best talents to broaden their market reach. On the other hand, Moshe Adler's (1985) theory shows that the success of superstars was motivated by popularity and benefitted from a snowball effect over time. In Adler's work, popularity explains the outsized success of some artists compared to others. With the expanding access to promotion and marketing tools, the theories of superstars remain valid, only augmenting the disproportions between the more niche musicians and the renowned artists. With the rise of AI, competing dynamics may intensify.

AI-powered tools, such as Suno, facilitate music production from beginning to end, and platforms like Ableton have started incorporating AI features to assist in composition, arrangement, and mastering. These technologies not only offer new creative possibilities to experienced musicians but may also enable individuals with no formal training to produce music. This could further democratize creation and expand the long tail. On the other hand, the same AI tools may also enhance the reach and productivity of superstar artists, reinforcing existing hierarchies.

The introduction of AI into the music industry invites revived scrutiny of the long-tail and superstar theories. AI might reduce production costs to near-zero, creating opportunities for mass entry into the market. It could also open new revenue streams, particularly for ambient or algorithm-friendly genres such as "study music," which are commonly featured in highly popular playlists. This raises fundamental questions for cultural economics, including the balance between intrinsic and extrinsic motivations in artistic labor (Caves, 2000). Moreover, the increasing quality of AI-generated content and the growing volume of such outputs may affect both supply and demand in significant ways.

The digitization of music in the early 2000s offers a useful parallel. Concerns over unauthorized copying predicted a decline in the quantity and quality of original works (Handke, 2012). Economists also warned that piracy would displace legal sales, undermining artist revenues (Liebowitz, 2006; Liebowitz, 2008; Rob & Waldfogel, 2006). Between 1998 and 2012, revenues in North America and Europe declined by 70–75%. However, production and distribution costs declined as well. Despite revenue losses, new music releases continued to grow until 2009, and consumer value increased due to the availability of a wider range of music (Aguiar & Waldfogel, 2018; Handke, 2012; Oberholzer-Gee & Strumpf, 2010).

In this context, the introduction of AI represents a potential continuation and intensification of digital trends. AI could further lower production barriers, invite participation from non-musicians, and create new monetization models. However, it also challenges core principles of cultural production, such as artistic intentionality and intrinsic value.

The line between human- and machine-made music starts to blur, which invites the long-standing debates in cultural economics about the purpose of art, the role of the process of creation, the structure of creative labor, and copyright laws to be once again re-evaluated.

3. Methodology & Data

3.1 Research Approach

Contrary to the earlier predictions for the music industry, digital copying and falling revenues in the primary market for sound recordings did not stop the growth of the supply of copyright-protected works (Aguiar & Waldfogel, 2018; Handke, 2012). Several years later, artificial intelligence emerged as a potential factor that might be crucial in the continued development of cultural sectors.

However, the music industry, although vastly inclusive toward new technological developments, only saw the first generative AI-powered music production programs emerge in 2016. This development occurred alongside expansive digitalization in the music industry and the global rise of music streaming platforms.

Following prior empirical research and broader industry trends, the growth of the supply of music recordings in the market was expected to follow a stable upward trajectory (Aguiar & Waldfogel, 2018; Handke, 2012). At the same time, AI is increasingly recognized as possibly disruptive for the cultural sector.

Based on this context, the following hypothesis is tested:

> H_0: The rate of growth in music recording supply does not significantly change following the introduction of generative AI into music production technologies.
> H_1: The introduction of generative AI into music production technologies is associated with significant change in the growth rate of music recording supply.

Certain musical genres are historically known for their usage of acoustic instruments with or without amplification and are generally characterized by limited use of advanced production technologies, such as in the case of jazz or classical music. To account for potential differences in technological adoption, five distinct genres will be analyzed to identify possible discrepancies in AI's impact across them. Accordingly, the following hypothesis is tested:

H_0: The introduction of generative AI into music production has no differential impact across genres; the change in supply is the same for both technology-dependent and traditionally acoustic genres.

H_2: The introduction of generative AI into music production has a different impact on genres that are technology-dependent (pop, techno, dance) compared to traditionally acoustic genres (classical, jazz).

Analyzing genre-specific data enables this study to capture possible heterogeneous effects of AI adoption across different musical styles, distinguishing between technology-intensive genres and those traditionally acoustic. This approach not only identifies whether AI has impacted music production overall but also highlights where its influence has been more pronounced. It shows in which specific subsectors AI might be facing some resistance or limited influence, allowing for a better understanding of its implications in genre-specific sections in the music industry.

Artificial intelligence is a technology promising a possible further development of digitalization strategies, such as improving access to musical products for consumers and democratization of music production with access to advanced music production programs (e.g., Ableton AI, LogicPro). These programs can automate significant parts of the song creation process, allowing artists to reduce production costs and making album production more accessible to entry-level musicians. It may lower the barrier to entry for non-professional, entry-level musicians who lack composition, production, or singing/songwriting skills, allowing them to produce songs using music-making AI programs, such as Suno AI.

However, despite these opportunities, the widespread integration of such tools is relatively recent, with the first music production AI-powered tools emerging in 2016. The full list of dates years for the introduction of each AI music production program ranges from 2016 to 2022 (see Table B1).

To investigate the impact of generative AI on music production output, this study employs a quantitative research approach based on secondary data analysis. The core method used is intervention analysis for short time series, developed by Tryon (1982), which is particularly suited when identifying significant structural changes in a time series when limited data points are available.

This method allows testing whether the introduction of generative AI tools in 2016 corresponds to a statistically significant change in the number of new recordings released annually. In line with previous approaches in cultural economics (e.g., Aguiar & Waldfogel, 2018), this paper analyzes global music release data obtained from MusicBrainz, focusing on the years before (2000-2015) and after AI's introduction (2016-2024). The raw data extracted from MusicBrainz for each individual release according to date was grouped into a group of releases counted annually (see Table A1).

To address genre-specific variation, the analysis includes five genres: pop, dance, techno, classical, and jazz, allowing for a comparison between technology-dependent and traditionally acoustic genres. The study employs a similar methodological approach to that of Handke (2012).

The time series is divided into two main segments:

1. The pre-period ranging from 2000 to 2015. In this period, as researched before (Aguiar & Waldfogel, 2018; Handke, 2012), the number of new works brought to the market has increased substantially since the 2000s, and the quality of new releases has grown since. The growth of the supply of new music recordings was stable until 2016.
2. The post-period (2016–2024), coinciding with the global emergence of AI music production tools used for track separation, mixing, mastering, composition, and, more recently, lyric generation through large language models.

The starting point of the time series is determined based on previous research and the global introduction of general music production software in the early 2000s. The endpoint is determined by data availability.

3.2 Data

The data used in this analysis are the number of new recorded music products released globally each year from 2000 until 2024, including genre classifications beginning in 2008, when genre data started to be uploaded. All data were sourced from the MusicBrainz database, an open music encyclopedia that compiles and publicly shares metadata related to music releases (MusicBrainz Foundation, n.d.-a). As of May 2025, MusicBrainz contains information on over 2.5 million artists, 4.7 million releases, 35.2 million recordings, and more than 2,000 genre entries (Musicbrainz Foundation, n.d.-c). For each release, metadata typically includes the artist's name, release title, release date, release country, and, from 2008 onward, genre data.

Regarding genres, before 2018 information was only available through the "tag" section. After 2018, genres received a separate field on MusicBrainz entity pages, making them distinguishable from general tags. Since 2020 genres have their own entity pages and a dedicated API endpoint. These developments affect the completeness and consistency of genre classification in the dataset. Because genre data initially appeared as user-applied tags, there is a possibility of missing genre information on some releases or genres not being classified consistently, particularly in data prior to 2020. This limitation is further discussed in the limitations section.

This paper serves as preliminary research into AI's role in the music industry and therefore focuses on a global trend in music release volume without disaggregating it by country. The global approach helps mitigate the issue of missing or inconsistent data in some regional samples from 2000 to 2024. As MusicBrainz is a crowd-sourced and open-access database, it is inherently subject to potential gaps or inconsistencies in data coverage.

Despite these concerns, MusicBrainz is widely used by digital music services, such as Spotify, YouTube, Google, and Amazon; by public broadcasters, such as BBC (Musicbrainz Foundation, n.d.-b), and by researchers (Aguiar & Waldfogel, 2018) making it authoritative enough to be a preferable data source for the time-series analysis done in this paper.

The dataset includes 3,152,388 releases grouped by year, from 2000 to 2024. Genre data are available for five different genres: classical, jazz, pop, techno, and dance.

Although reliance on a single data source introduces some limitations, time restrictions do not allow for triangulation of data with additional databases. The widespread academic and industry use of MusicBrainz supports its reliability for the scope of this paper. This issue is further addressed in the limitations section.

The dataset consists of the 25 consecutive years of global release counts. The sample was extracted from MusicBrainz using the MusicBrainz Web API. A custom extraction script was written in Python (version 3.10) and executed using the PyCharm IDE. The script performed a series of API calls to retrieve all release groups between January 1, 2000, and April 28, 2025. For each release group, the following fields were collected:

- Artist name
- Release ID
- Release title
- Release date
- Release Country
- Tag list
- Genre (for releases from 2020 onward)

Data cleaning steps included the exclusion of entries missing a valid release date, extraction of the correct release date of re-releases issued after 2000, and grouping all releases into yearly totals of release groups including exclusion of year 2025 for its lack of full-year data.

3.3 Research Method

The statistical method used in this paper is an intervention analysis for short time series, developed by Young (1941). This approach is particularly well-suited for bivariate socio-economic conditions, particularly when the setting resembles an archetypal set-up of a natural experiment (Cook et al., 1979; Handke, 2012).

Importantly, the variation in the independent variable needs to be significant, and the supposed relationship between the independent (AI introduction) and dependent (the annual number of new music recordings released) variables needs to be strong. Additionally, the number of observations should fall between 8 and 49, a range within which more sophisticated statistical models may be unreliable (Young, 1941).

In this context, the method is used under the assumption that the artificial intelligence introduction might be a strong external shock for the music industry, one that may possibly lead to severe adverse consequences.

Tryon (1982) proposes a method to test for a significant deviation between consecutive periods of shorter time series. The *C* statistic, originally developed by Young (1941) and adapted by Tryon (1982) and Handke (2012), is used to test for non-random variation in the time-ordered data series.

It is calculated as follows:

$$C = 1 - \frac{\Sigma_{t=1}^{n-1}(y_t - y_{t+1})^2}{2\Sigma_{t=1}^{n}(y_t - \bar{y})^2}$$

In the formula, y_t represents the value of the time series at a point in time *t.*

The *C* statistic is used to compare two measures of the variance of an ordered set of data, the one that depends on the mean, such as the denominator in the equation above, and the one that does not, such as the numerator in the same equation. The *C* statistic provides a measure of the variability relative to its slope (Tryon, 1982), it also offers a method to determine the probability of whether the expressions of a time series vary randomly around their mean (the null hypothesis) or whether the series contains a significant slope or shift in the mean after a specific point in time (Handke, 2012; Sheskin, 2003; Tryon, 1982; Young, 1941).

In this research, the method should show the probability with which the post-AI supply of music recordings contains a statistically significant disturbance, slope, or shift in the mean after AI's introduction in 2016, or as stated in the null hypothesis, the expressions of the time series vary randomly, meaning they do not show any shift in the mean.

Hence, calculating the *C* statistic for the pre-AI period (2000-2015) and for the pre- and post-AI periods is done to understand if the yearly music release counts show non-random structure. If the data are random, the difference from one point to the next should not follow a consistent pattern, with a *C* value close to zero. In case the *C* statistic shows a value above 0, it suggests a trend. The *C* statistic will also be used to test if the introduction of generative AI into music production has no differential impact across genres and the possible change in supply is the same for both technology-dependent and traditionally acoustic genres.

To determine the statistical significance of the observed *C* value, the standard error of *C* (Sc) is computed using

$$\mathrm{Sc} = \sqrt{\frac{\mathrm{n}-2}{(\mathrm{n}-1)(\mathrm{n}+1)}}$$

In this context, *n* is the number of observations. The *C* statistic is then converted into a standardized *Z* statistic:

$$\mathrm{Z} = \frac{\mathrm{C}}{\mathrm{Sc}}$$

The *Z* statistic allows the comparison of *C* to a standard normal distribution. Moreover, it allows for a formal test of the null hypothesis (H_0) that the sequence is random. If $Z > 1.65$ (Young, 1941), the null hypothesis can be rejected at the 1% significance level. The 1% significance level is chosen considering methodology and robustness of the findings. Young (1941) reports significance levels at both 5% and 1% thresholds. The author recommends using stricter significance levels to reduce the change of falsely detecting structure where it does not exist, hence the decision to choose 1% significance levels.

In this study, significant *Z* values are to provide evidence supporting the alternative hypotheses (H_1 and H_2), indicating a structural shift in the number of new music recordings or differential effects across genres.

Compared to OLS regression, tests based on the *C* statistic often offer higher statistical power and are less prone to bias from autocorrelation or small-sample non-normality (Tryon, 1982; Young, 1941). However, the *C* statistic cannot specify the form of any detected change: it neither distinguishes between a slope alteration and a sudden level shift nor quantifies the effect size, nor indicates whether an intervention's impact is abrupt or gradual, temporary or permanent.

Furthermore, to facilitate a valid comparison, the pre-intervention time series must be trend-free. Since the original pre-period data for the “new releases” series exhibit a trend, they are first transformed to achieve stationarity before proceeding with the intervention analysis, where there is no significant deviation from random variance according to the *C* statistic.

4. Empirical Analysis & Results

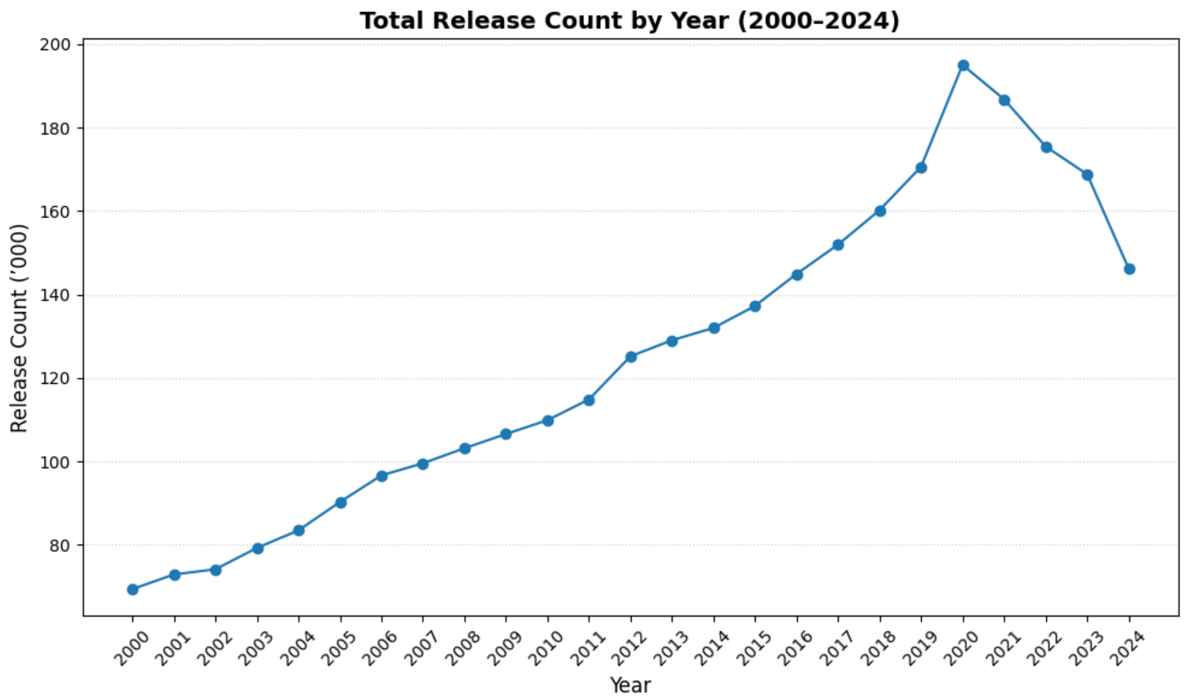
Figure 1 shows a time series for the number of new recordings released globally. The time series regards 25 observations for the same number of years between 2000 and 2024. The first 16 observations from between 2000 and 2015 are from the pre-period, as shown in the “Research Approach” section. The 9 observations between 2016 and 2024 are from the post-AI period, corresponding to the period following the introduction of generative AI tools. The dashed vertical line separates the two periods.

A visual inspection of the entire time series shows that the trend in the supply is upward-going throughout the period. However, a noticeable peak appears in 2020. From 2021 onwards, a slight decrease is observed. As a preliminary caution, it is important to notice that oftentimes it takes more than a year for the full release data to be uploaded to the MusicBrainz dataset, which can be considered one of the possible factors accounting for supply decrease in the last three years.

Except for a big jump in 2020, there are no obvious interruptions in the supply line from the post-AI period. The last full period covered - 2024, counts for 6.5% of releases, more than at the end of the pre-AI period - 2015. Moreover, the mean score for new releases post-AI is 50.7% greater than the mean from the pre-AI release period.

Figure 1

The number of new releases released yearly globally



To determine whether the post-AI period shows a significant structural break from the earlier trend, an intervention analysis is conducted, using the *C* statistic developed by Young (1941) and applied by Tryon (1982) and Handke (2012).

Throughout the whole first quarter of the 21st century, the supply of new music releases globally is rising; however, what remains a question in this context is if the growth stayed as stable after 2016 as in the pre-AI period, or were there any substantial differences after the introduction of AI tools for music production in 2016 that would considerably change the pattern of growth from the pre-AI period?

Just as in Handke (2012), the release series in this paper has a pronounced linear trend in the 2000-2015 period. To guarantee stationarity, the trend from the pre-AI era must be eliminated before using the *C* statistic. To isolate the AI "shock" in 2016 from the underlying growth, the proposed de-trend happens in two ways. First, the estimation of an OLS trend on pre-2016 data and the application of Tryon's (1982) *C* statistic to the residual series. Second, the *C* statistic intervention is performed on the first difference of the series. In both of those cases, a significant *C* around 2016 would indicate a shift above the ordinary expansion of the market.

4.1 Regression model identification

Tables 1a and 1b report standard regression models estimated for the 16 observations from the pre-AI period. Following Handke's (2012) approach, multiple OLS models were estimated for the pre-AI period (2000-2015). The linear model yielded one of the highest R^2 values (0.992) and the highest *F* ratio (1750.565), indicating the best fit among all the tested models. Despite the simplicity of the linear model, it was preferred over more complex quadratic and cubic models that showed similar R^2 values (Quadratic: R^2 = 0.994; Cubic: R^2 = 0.994). A simple regression model is preferred in this analysis because it performed as well as more complex models.

Table 1a

OLS regression results for new releases during the pre-AI period (2000-2015)

Equation	**Model summary**				
	R^2	F	df1	df2	Sig.
Linear	0.992	1750.565	1	14	.000
Logarithmic	0.845	76.071	1	14	.000
Inverse	0.503	14.148	1	14	.002
Quadratic	0.994	1009.688	2	13	.000
Cubic	0.994	624.652	3	12	.000
Compound	0.991	1487.504	1	14	.000
Power	0.897	121.300	1	14	.000
S-curve	0.570	18.527	1	14	.000
Growth	0.991	1487.504	1	14	.000
Exponential	0.991	1487.504	1	14	.000
Logistic	0.609	21.850	1	14	.000

Table 1b

OLS regression results for new releases during the pre-AI period (2000-2015)

Equation	**Parameter estimates**			
	Constant	b1	b2	b3
Linear	62042.400	4638.320	-	-

Logarithmic	51973.640	25818.836	-	-
Inverse	115258.628	-65266.412	-	-
Quadratic	64314.436	3880.975	44.550	-
Cubic	64795.132	3585.480	86.716	-1.654
Compound	66721.232	1.047	-	-
Power	59376.057	0.267	-	-
S-curve	114943.051	-0.698	-	-
Growth	66721.232	0.046	-	-
Exponential	66721.232	0.046	-	-
Logistic	7.506	-0.862	-	-

Note. t = 1 in 2000.

Figure 2a shows the observed annual release counts (in blue) versus the pre-AI fit straight line (orange) estimated on the data from 2000-2015. After the intervention point, it is visually observable that the blue curve diverges from the previous pattern.

The model for figures 2a and 2b is a visual representation of the results of intervention analysis for "new releases", based on linear OLS regression for the pre-AI period presented in Table 3. The blue line is a representation of an actual yearly count of releases. The orange line is a predicted growth value based on the pre-AI period analysis (Model prediction *e* in Table 3). A red vertical line shows the year for the introduction of AI. Both figure 2a and figure 2b clearly show that the real scores deviate from the predicted line. In the case of figure 2b, the model is based on the residuals from the pre-AI trend. Similarly to Figure 2a, the horizontal black line represents the predicted pattern. As seen by the blue values, starting in 2016, they begin to deviate strongly from 0. It is visually observable that prior to 2016 the residuals scatter tightly around zero, confirming the adequacy of the straight-line baseline. After 2016, the pattern changes by first growing large and positive from 2017 to 2021, then later shifting to negative from 2023 to 2024, which shows a difference compared to the pre-AI growth pattern.

Figure 2a

Linear model for new releases against the fitted pre-AI linear trend

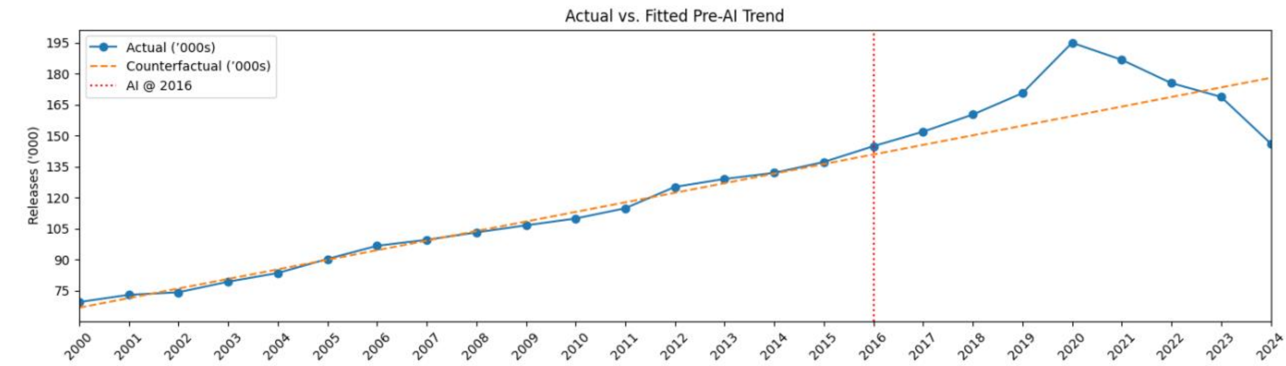


Figure 2b

Residuals for the pre-AI linear model

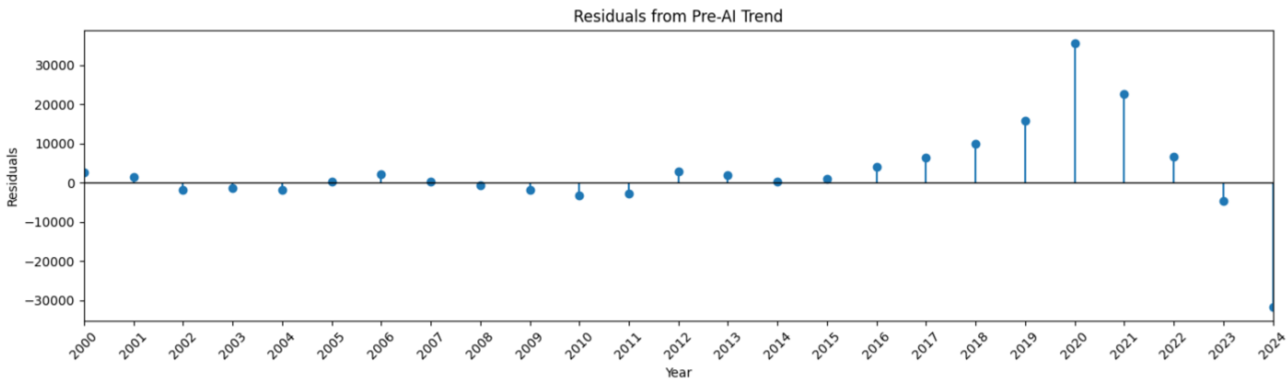


Table 2 compares the linear model with the quadratic and cubic models, based on Handke (2012), to see which one fits the data best by looking at the highest R^2 value. Table 2 focuses on the comparison between linear, quadratic, and cubic forms. The table compares the fit of the regression models using the explained sum of squares (SS(X)). It represents the portion of the total variance in the dependent variable accounted for by the model. Higher SS(X) values should indicate a better fit, and the *F* test assesses whether more complex models provide a statistically significant improvement over the simple ones (in this case, linear). Linear, quadratic, and cubic forms are chosen based on their highest R^2 values: linear - $R^2 = 0.992$; quadratic - $R^2 = 0.994$; cubic - $R^2 = 0.994$. In Table 2, the *F* ratio between linear and quadratic, linear and cubic, and quadratic and cubic is calculated, showing the highest value for the ratio between linear and quadratic forms.

However, none of the comparisons holds a statistically significant *p*-value, which is calculated for each couple as well.

Table 2

F test to compare the fit of the models of new releases

Equation	df	SS(X)	*F* ratio	p-value
Linear	14	58,499,251	Linear-quadratic 3.12	.10
Quadratic	13	47,162,773	Quadratic-cubic 0.06	.81
Cubic	14	58,499,251	Linear-cubic 1.48	.27

Although both quadratic and cubic models achieve a marginally higher R^2 than the linear model, none of the added terms shows a statistically significant improvement over the simple linear trend (all $p > 0.05$). Therefore, the residuals of the linear model are analyzed, chosen based on the linear model's parsimony.

As mentioned in Handke (2012), the linear model might prove itself problematic on a theoretical level, predicting negative values for the longer time series. Any regression model will be unlikely to provide any valid predictions for more than a short timeframe. That shows itself as a reminder that this intervention analysis must remain within the sample period of 2000-2024.

4.2 Intervention analysis of regression model residuals

Following Handke (2012), the *C* statistic is applied to the residuals from the pre-2016 OLS trend to formally test for a structural break coinciding with the introduction of AI to music production programs. The computed *C* statistic is as follows:

$$C = 1 - \frac{\Sigma_{t=1}^{n-1}(\hat{\varepsilon} - \hat{\varepsilon}_{t+1})^2}{2\Sigma_{t=1}^{n}(\hat{\varepsilon}_t - \bar{\varepsilon})^2}$$

The numerator of the *C* statistic is the sum of squared first difference values for the residuals, and the denominator of the *C* statistic is the sum of the squared differences between the residual for each year and the mean of all residuals in the period multiplied by two. In the model, $N = 26$ for the total span for the years 2000-2024. Moreover, the standard error (S*c*) and the Z statistic are calculated as illustrated in the equations in paragraph 3.2. Under the null hypothesis of no intervention, Z is approximately standard normal: Z>1.65 and rejects at the 1% level.

For each year of the time series, both from the pre- and post-AI periods, the expected e_t value from the regression model is subtracted from the value that is observed (y_t) to generate the value in relation to the linear trend during the pre-AI period $\hat{\varepsilon}$ (see equation below). Thus, table 3 shows the results of the analysis of the residuals of the linear model for the time series of "new releases".

$$y_t - e_t = \hat{\varepsilon_t}$$

Table 3 registers two tests. First, the test for the pre-AI period is run to understand whether the residuals of the linear model contain no significant trend. The resulting Z statistic is not significant ($Z = 1.9091 < 2.2423$) at 1%, indicating a random structure. This result shows that the linear model fully removes the trend. However, to assure analytical robustness, a first-difference intervention analysis for "new releases" on the pre-AI period data is calculated as well.

After the first calculation for the pre-AI period, the test for the entire time series is conducted to examine whether the values observed deviate from the ones of the pre-AI period. The mean of the residuals in the period of AI usage is higher than the mean for the pre-AI period (64,848). The Z statistic for the time series for pre- and post-AI periods is significant ($Z = 3.7166$). That means there is significant evidence for a growth pattern in the number of new releases published each year during the post-AI period.

Table 3

Intervention analysis for "new releases", based on linear OLS regression for the pre-AI period (2000-2015)

	Year	**Score *y***	**Model prediction *e***	$\boldsymbol{\hat{\varepsilon} = y_t - e_t}$	
Pre-AI period	2000	69,386	66,681	2705	pre-AI period:
	2001	72,904	71,319	1585	
	2002	74,145	75,957	-1812	($\hat{\varepsilon}$ for pre-AI
	2003	79,258	80,596	-1338	period is 0)

	2004	83,465	85,234	-1769		
	2005	90,265	89,872	393	*C* = 0.4473	Pre-AI and
	2006	96,642	94,511	2131		post-AI period:
	2007	99,554	99,149	405	*Sc* = 0.2343	
	2008	103,147	103,787	-640		($\hat{\varepsilon}$ for post-AI
	2009	106,563	108,426	-1863	*Z* = 1.9091	period is 64,848)
	2010	109,876	113,064	-3188	Not significant	
	2011	114,844	117,702	-2858		*C* = 0.7135
	2012	125,179	122,341	2838		
	2013	129,032	126,979	2053		*Sc* = 0.1920
	2014	131,980	131,617	363		
	2015	137,250	136,256	994		*Z* = 3.7166
Post-AI	2016	144,909	140,894	4015		Significant
period	2017	151,942	145,532	6410		
	2018	160,203	150,170	10,032		
	2019	170,590	154,809	15,781		
	2020	194,999	159,447	35,552		
	2021	186,751	164,085	22,665		
	2022	175,454	168,724	6730		
	2023	168,807	173,362	-4555		
	2024	146,218	178,000	-31,782		

Note. The linear OLS regression model for 'new releases' during the pre-AI period ($t = 1$ in 2000) is $y = 62042.40 + 4638.32t$. For the Z statistic, the critical value at 16 observations and the 5% level of significance is 1.6492, and for the 1% level of significance, it is 2.2423. The critical value at 25 observations for the 5% level of significance is 1.6484, and for the 1% level of significance it is 2.2717 (Young, 1941).

4.3 Differenced time series analysis

Following the analysis proposed by Tryon (1982), the *C* statistic intervention is performed on the first difference of the series. It has the advantage of eliminating the deterministic trend component, therefore avoiding model-selection judgments, but at the cost of losing some data in the process of differencing.

In line with Tryon (1982), the intervention analysis requires that the pre-intervention time series be free from any systematic trends or non-random structure. In this study, the residuals from the linear regression model fitted to the pre-AI period (2000-2015) show a statistically non-significant *Z* value based on the *C* statistic. The results allow for the assumption of randomness required for the comparison baseline. However, in order to check for robustness of results for the analysis, the time series is calculated based on the intervention analysis of the differences in time series, using first differencing. That eliminates any linear trends by measuring the change in values from one year to the next. This, in turn, allows the intervention analysis to be conducted on a stationary series, ensuring that any structural change that is detected post-AI reflects a deviation from a pattern and not a continuation of an existing trend.

Figures 3a and 3b show the observations for the "new releases" time series and its first difference $\Delta^1 y$. Table 4 shows the results of the intervention analysis for the differenced time series. The result for the *Z* statistic is 0.2816, which is not significant (for $Z = 2.2369$ at 1% level of significance). This confirms that the pre-AI period is suitable as a baseline for the analysis of the full time series. While applied to the full time series, the *Z* value becomes significant ($Z = 2.6656$ for critical value $Z = 2.2700$ at 1% level of significance), indicating that the introduction of AI tools in 2016 coincides with a structural shift in the growth dynamics in the music supply, disrupting the prior pattern.

This result indicates that there is significant evidence for a structural change in the growth pattern of new releases in the post-AI period, rejecting the null hypothesis that the rate of growth in music recording supply does not significantly change following the introduction of generative AI into music production technologies.

Table 4

Intervention analysis for "new releases", based on first difference

Year	Score y	First difference $\Delta^1 y$

Pre-AI period	2000	69,386	-		
	2001	72,904	3518		
	2002	74,145	1241	Pre-AI period:	
	2003	79,258	5113		
	2004	83,465	4207	(mean for $\Delta^1 y$ during	
	2005	90,265	6800	pre-AI period is	Pre-AI and post-AI
	2006	96,642	6377	4524)	period:
	2007	99,554	2912	C = 0.0678	
	2008	103,147	3593		(mean for $\Delta^1 y$ during
	2009	106,563	3416	Sc = 0.2409	post-AI period is
	2010	109,876	3313		3201)
	2011	114,844	4968	Z = 0.2816	C = 0.5214
	2012	125,179	10335	Not significant	
	2013	129,032	3853		Sc = 0.1956
	2014	131,980	2948		
	2015	137,250	5270		Z = 2.6656
Post-AI period	2016	144,909	7659		Significant
	2017	151,942	7033		
	2018	160,203	8261		
	2019	170,590	10387		
	2020	194,999	24409		
	2021	186,751	-8248		
	2022	175,454	-11297		
	2023	168,807	-6647		
	2024	146,218	-22589		

Note. For the Z statistic, the critical value at 15 observations and the 5% level of significance is 1.6493, and for the 1% level of significance it is 2.2369 The critical value at 24 observations for the 5% level of significance is 1.6484, and for the 1% level of significance it is 2.2700 (Young, 1941).

Figure 3a

Documentation of first difference scores for 'new releases' observations and their first difference scores ($\Delta^1 y$)

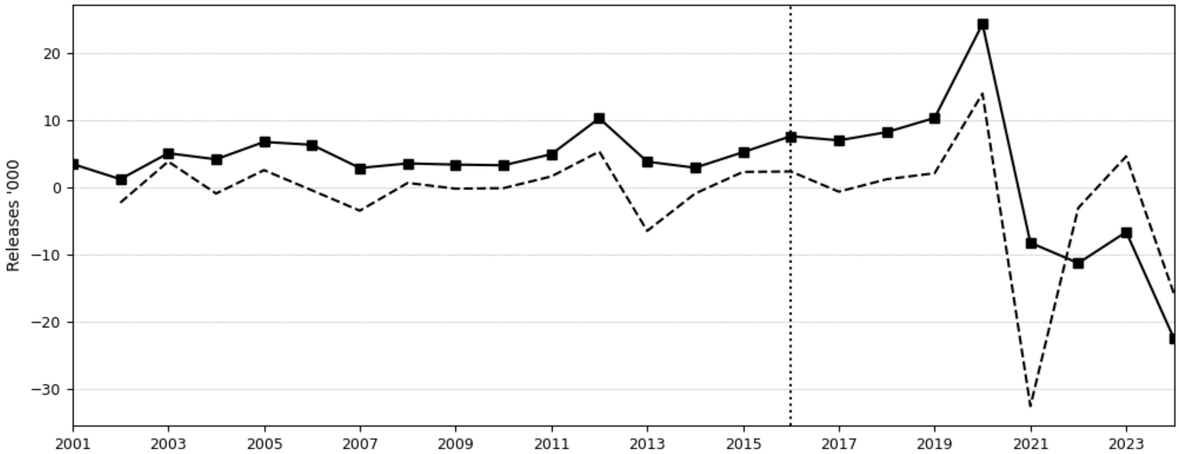
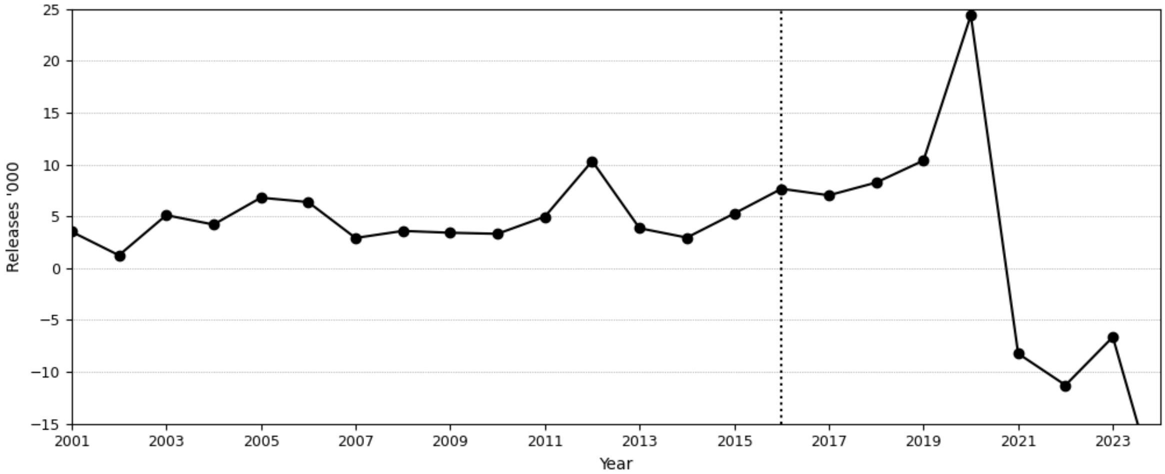


Figure 3b

First difference scores enlarged



4.4 New releases and genres

The chosen genres for the interpretation of the results for new releases in music supply post-AI were classical, jazz, pop, dance, and techno. They were selected to show what possible effects the introduction of AI in music production technology could have on each of them. Moreover, the supply of some types of genres was proposed to be less affected by digital copying in Handke (2012) and the following analysis was partially inspired by the previous changes to the music industry.

Table 5 displays the annual count for each specified genre from 2008 to 2024. The reduction in the years shown in the table is dictated by the availability of data in the MusicBrainz dataset. Figure 4 is a visual representation of the table, showing in the graph the line of yearly releases depending on the genre.

Table 5

Releases per year by genre

Year	Pop	Jazz	Classical	Techno	Dance
2008	30,867	8324	2045	3581	770
2009	37,486	12,211	3042	8643	1619
2010	7195	2346	730	1832	326
2011	5773	1828	606	930	318
2012	29,061	10,147	4802	4679	1739
2013	9988	2842	2574	1059	550
2014	12,235	3342	3074	1533	822
2015	13,634	4053	3861	2259	1131
2016	15,010	4524	4630	1834	1464
2017	19,771	7107	6724	2641	1856
2018	24,481	8742	5150	3580	2198
2019	27,716	10,429	6208	5703	2410
2020	42,283	13,438	7994	6765	3844
2021	37,191	19,031	7068	7054	4632
2022	18,726	102,98	4071	4338	3585
2023	12,594	5884	2543	2129	1168
2024	9687	2620	2428	1473	1058

Table 6

Intervention analysis for "genres", based on linear OLS regression for the pre-AI period (2008-2015)

		Pop	**Jazz**	**Classical**	**Techno**	**Dance**
pre-AI period	β_1	-2562.13	-767.08	269.04	-516.35	7.55
	R^2	0.26	0.22	0.20	0.23	0.001
	C	-0.1848	-0.3425	-0.2639	-0.4105	-0.4365
	Sc	0.3086	0.3086	0.3086	0.3086	0.3086
	Z	-0.5989	-1.1100	-0.8554	-1.3303	-1.4147
		Not significant	Not significant	Not significant	Not significant	Not significant
post AI period:	$\hat{\varepsilon} = y_t - e_t$ mean post-AI residuals	26,549.238	10,002.805	323.123	5270.869	1494.702
pre-AI and post-AI period:	C	0.7391	0.7342	0.5407	0.7015	0.6724
	Sc	0.2282	0.2282	0.2282	0.2282	0.2282
	Z	3.2390	3.2173	2.3695	3.0741	2.9464
		Significant	Significant	Significant	Significant	Significant

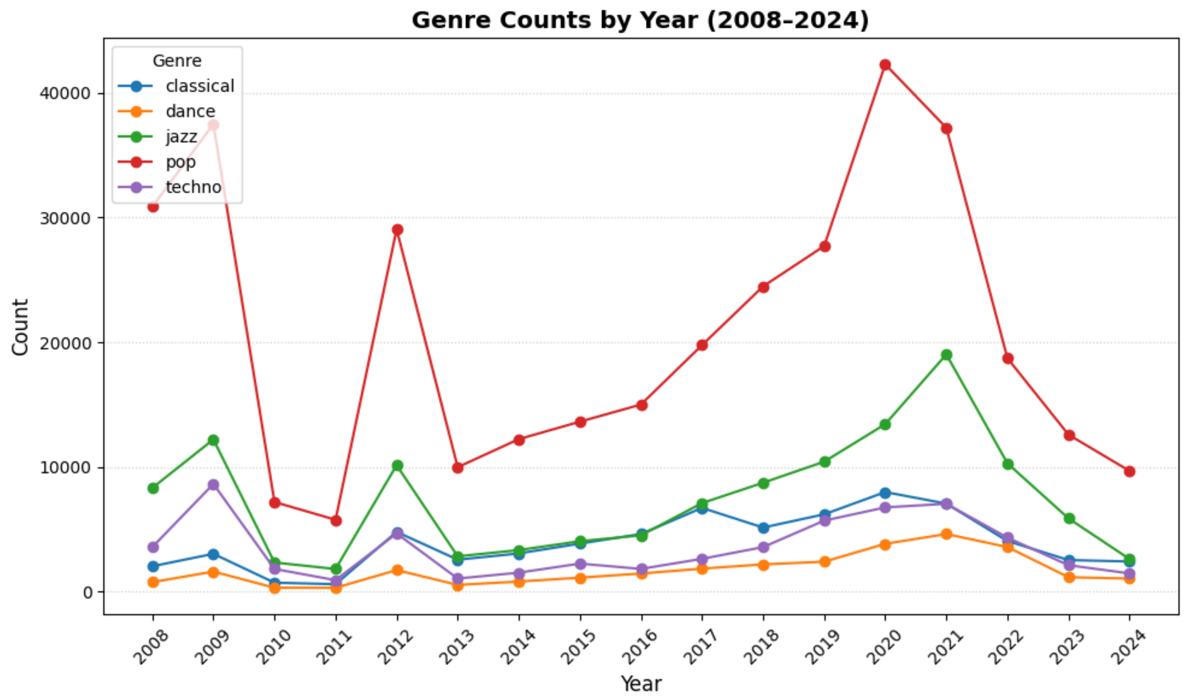
Note. The linear OLS regression model for 'genres' during the pre-AI period (t = 1 in 2008) is: for pop, y = 29809.46 - 2562.13t; jazz, y = 9088.50 - 767.08t; classical, y = 1381.04 + 269.04t; techno, y = 5388.11 - 516.35t; dance, y = 875.36 + 7.55t. For the Z statistic, the critical value at 8 observations and the 5% level of significance is 1.6486, and for the 1% level of significance it is 2.2423. The critical value at 17 observations for the 5% level of significance is 1.6492, and for the 1% level of significance it is 2.2470 (Young, 1941).

The reduction in the years shown in the table is dictated by the availability of data in the MusicBrainz dataset. As mentioned in the Methodology & Data section, the genre as a separate entity exists only from 2020, when it was introduced as a separate characteristic of each release.

Prior to that, each genre description was a part of the "tag" system, making it one of many tags that each release could receive, therefore in the same way less distinguishable from other tags in the MusicBrainz dataset. Consequently, the extraction of genre data can begin from the year 2008, when genres could be extracted separately from other tags associated with each release. The remaining data is valid and may reveal additional general findings that could be useful in preliminary research on AI and the music industry. The genre specification in table 5 confirms that overall counts climbed steadily from 2008 through about 2019 and began to run down around 2022-2024. Pop dominates in volume, jumping from around 7,000 releases in 2010 to around 42,000 in 2020. Classical shows a similar shape - low hundreds in the early 2000s and rising past 6,000 and 7,000 by the 2020s, with dance remaining at much smaller levels (peak numbers around 5 000). As shown in figure 4, pop is a genre that dominates throughout the whole measured period, while dance and techno are the two lowest in supplied releases.

Figure 4

Releases per year by genre



In order to assess whether the structural impact of AI on music supply varies across genres, the intervention analysis was replicated separately for each of the five genres. The same methodological approach was followed as for the overall time series, using the intervention analysis for genres based on linear OLS regression for the pre-AI period (2008-2015), applying the *C* statistic to test for non-random structural changes after the 2016 AI introduction.

Table 6 summarizes the results. For each genre, the *Z* statistic was calculated based on the pre- and post-AI periods. In the case of all genres, the *Z* statistic shows insignificance for the pre-AI period, making the intervention analysis a valid form to ensure that the pre-AI time series exhibits no significant trend.

Based on the pre-AI and post-AI periods, all cases show that the *Z* value exceeds the 1% threshold (2.2470 at 1% significance) from Young (1941). That indicates a statistically significant change in the structure of annual supply for all the genres: pop, classical, jazz, techno, and dance. The result suggests that the introduction of AI coincided with a disruption in the previously stable growth pattern for all five genres.

Among technology-intensive genres, pop and techno exhibit the strongest values (pop: $Z = 3.2390$; techno: $Z = 3.0741$), suggesting that AI tools may have played a more important role in altering the supply trends in these genres than in dance, which has a value *Z*

= 2.9464. Interestingly, both jazz and classical show significant Z values, with jazz Z = 3.2173, the closest to the value of the pop genre. This suggests that the integration of AI into the music production process may impact even traditionally more acoustic genres. Classical music shows the smallest Z value with $Z = 2.3695$ potentially underlining lower levels of AI adoption in the classical music genre or slower structural adjustment.

The results shown in this section do not reject the null hypothesis (H_0), showing that the introduction of generative AI into music production has no differential impact across genres; the change in supply is the same for both technology-dependent and traditionally acoustic genres. Based on the results, it is important to mention that all the genres saw a significant value, which in turn connects to a potential structural break for all genres, not only technology-dependent ones. Although classical music has its Z value at the lowest level, it was considered statistically significant nevertheless. Moreover, jazz, considered an acoustic genre, showed a value closest to that of pop, undermining the possible null hypothesis rejection.

Although the genre-specific trend difference values suggest certain distinctions, they all prove statistically significant values for a structural break after the AI introduction in the music production tools.

These results show some preliminary signs that gaining access to datasets with more detailed genre specifications for each globally published release, along with potentially longer timespans, could provide better opportunities to analyze the possible relationships between the genres discussed in this thesis more deeply.

5. Discussion of results

The intervention analysis conducted in this paper shows strong evidence that the introduction of AI-powered music production tools in 2016 corresponded with a statistically significant upward shift in the global supply of new recordings. The application of Tryon's C statistic to the residuals from the pre-AI linear trend showed Z scores strongly exceeding the 1.65 threshold for every year from 2016 until 2024 (Table 3). Further, the first-difference approach confirmed these findings, with high Z scores even after eliminating deterministic trends (Table 4). The results mentioned show that we can reject the null hypothesis (H_0) that growth in the supply of new recordings remained unchanged following AI's arrival in the music industry, and support the alternative hypothesis (H_1), indicating a significant change in growth patterns starting in 2016.

The genre-level analysis reveals that the production growth does not necessarily tie itself to the strict genre specificity. Although pop showed the highest Z score among all genres ($Z = 3{,}2390$), jazz, a traditionally acoustic genre had almost the same value at 1% level of significance ($Z = 3{,}2173$). More research on genre-specific data is needed and encouraged to better understand the play between different genres in production growth.

Especially as Large Language Models (LLMs) have only recently begun to lower the cost and time of lyric writing, their impact on lyric-centric genres merits particular attention. In the case of this research, the recency of LLM AI models, such as ChatGPT, which was released only at the end of 2022, makes the analysis difficult as a consequence of the scarcity of data available.

Regarding genre data, other limitations include the lack of availible data preliminary to 2008. Data extracted from MusicBrainz is fully done by the users, which further limits the scope of genre data - data extraction included words based on genre names, such as words of genres: “pop”, “jazz”, “techno”, “dance”, “classical” and possible combinations of words tied with the main genre names by a hyphen, or words that include the official name of the genre within the name itself. However, the scope of the programming script might have missed other possibilities. In turn, the scope of the search for the releases based on genre information done through Python program might have limited the acquired data.

The results correspond to the previous findings regarding digitalization in the music industry (Aguiar & Waldfogel, 2018; Handke, 2012), further proving the rise in the production side of music recordings. However, the results indicate a pronounced growth since 2016, which could potentially confirm the preliminary theoretical disputes of AI’s disruptive impact on creative industries (Amankwah-Amoah et al., 2024), driving the scientific research further into the role of AI in productivity in the music sector and possible effects associated with this phenomenon.

The analysis in this paper finds a significant impact of AI technology on the supply of music releases globally between 2016 and 2024. It has been less than ten years since AI was introduced into music production programs. The results shown in the analysis underline the possibly impactful nature of AI technology across industries; however, in this case, it is specified in the supply of music recordings.

Methodological approach chosen in this paper allows for the usage of smaller datasets. It is, however, important to mention that although suitable in this case, intervention time series methodology cannot isolate whether the AI or anything else yielded the results. Although it is known that the “shock” happened around the time of the introduction of the first music production AI programs, it does not allow for certainty, which ought to be considered as a limitation in the methodology. Moreover, in connection to time limitation, the robustness checks accounting for a year before or a year after the proposed date of AI technology introduction were not completed.

Another limitation is the singular source of data. The MusicBrainz datasets are thorough and used across the industry; however, they are limited in their scope, which shows itself as a limitation to the data restrictions requirement.

6. Conclusion

This paper aimed to investigate whether the introduction of generative artificial intelligence (AI) tools in music production has had a measurable impact on the global supply of recorded music. Drawing on the intervention analysis pioneered by Tryon (1982) and applied to the music industry by Handke (2012), a new time series was assembled of annual release counts from 2000 to 2024 using MusicBrainz metadata. It was then evaluated whether the introduction of AI production programs around 2016 coincided with a structural change in the growth trajectory, against the steady pre-2016 upward trend.

The empirical analysis proceeded in three main parts. First, an ordinary least squares (OLS) regression was fitted to the pre-AI 2000-2015 segment, and the residuals were examined against the fitted line. In this segment, both the *C* statistic and its first-difference version showed *Z* scores strongly exceeding the 1.65 threshold in pre- and post-AI period, showing a highly significant increase in release counts as a non-random fluctuation around the old trend. Secondly, the *C* statistic was repeated on the differenced series, eliminating any deterministic trend and confirming the intervention results. Next, a genre-specific analysis was done, including genres more prone to technological changes, such as pop, techno, and dance, and genres historically opposite to that trend, such as classical music and jazz. The *C* statistic for each genre for pre- and pre- and post-AI period was done, testing the difference of each genre for statistical significance. Although pop and jazz showed the highest significance, all the genres have results bearing significance for a “shock” in the time series.

The findings for music releases support the alternative hypothesis (H_1), that AI’s arrival in music production coincided with an acceleration in the global supply of new recordings - a shock of significant magnitude. The pattern seen in this analysis in some way mirrors Handke’s (2012) results for digital copying “shock” in the 2000s, but in this case the presupposed idea does not come from expectancy for the decrease in the supply of music recordings together with the rise of digital copying.

The findings considering genre-related releases rejects alternative hypothesis (H_2), showing that all genres chosen to be analyzed (pop, jazz, classical, techno, and dance) show significant results. This, in turn, shows that AI introduction might have had impact on genres even not technologically dependent, such as jazz and classical music.

The robustness of the methodology indicated by significant *C* statistics on both residuals and differenced data provides some confidence that the observed shift is likely not a byproduct of sample bias or correlation, but rather indicates a genuine market change.

6.1 Contributions

This thesis contributes to the scholarly dispute by extending the intervention analysis into the rapidly evolving realm of AI-driven creative labor. Moreover, it provides one of the first assessments on the global scale of AI's impact on the supply side of the music industry, in some way complementing research done in different fields (Brynjolfsson et al., 2023; Dohmke et al., 2023).

By successfully using open metadata from MusicBrainz, this work demonstrates the feasibility of constructing long-run, large datasets of global release series and genre-specific counts with the help of programming software, such as Python. This way of gathering data expands the possibilities of research in the field of music and allows for further empirical research on artificial intelligence's role in cultural economics.

In the context of policymaking and brought to the attention of industry stakeholders, the results carry meaningful results, allowing for both possible enthusiasm and needed caution.

Bound to the theory of the long tail (Anderson, 2006), it is possible to draw some preliminary ideas on the suggestive evidence that AI tools might have further lowered technical and financial barriers to the production of music, enabling starting and more career-pronounced artists to bring more music content to the market with possibly lower costs of production by allowing for automation in many areas.

With further promise of democratization of the music sector globally, the results could be a promising sign that AI may further enrich customer's choice and expand the niche genres market. However, this perspective is rather one-sided, as the reality continues to demonstrate that a small number of artists dominate the market and earn a disproportionate share of revenues in the sector (Coelho & Mendes, 2019).

On the other hand, until now, there are no legal requirements to assign music creation or assistance in music production to AI, showing a clear lack of transparency for consumers and music makers. Following the official letters of music organizations (e.g., Culture Action Europe) regarding legal inquiries of the AI Act in Europe, there is seemingly a disagreement of music workers with AI’s usage of existent music data and copyright issues that are tied to it.

Moreover, the pronounced spike in supply in 2020 highlights the possibility of factors other than AI to confound the analysis done in this research, which ought to be acknowledged. This shows that, however successful, analysis results do require a very careful assessment and contextual approach.

6.2 Limitations

Several factors that limit the scope of this research ought to be mentioned. First, MusicBrainz, while authoritative and widely used in the sector in general, remains a crowd-sourced database, and it is possible that it underrepresents releases in certain regions, years, or with notice, genres.

In this context, especially the recent years' data is still being added. Second, the genre tagging in MusicBrainz only became systematically separate from user tags in 2020, making years prior to that relying on imperfect “tag” associations, leading to much smaller sample size for genre data and noisier estimates. Third, the post-AI period spans only ten observations, which limits in some ways the power of the findings.

Finally, AI introduction in this paper was treated as a single “shock” event, an intervention happened in 2016. It is, however, important to mention that the adoption of individual AI tools occurred in a more scattered way, and with the abrupt development of large language model technologies, the availability of programs keeps expanding. Moreover, it is impossible to distinguish AI from other influences that might have driven the supply in music recordings and occurred at the same time as AI tools development.

6.3 Future Research

Building on the previously mentioned limitations, future studies could expand data sources and integrate the releases to cross-validate global trends between different data sources, including a differentiation between countries and regions. Another possible angle is refining genre classification, allowing for more consistent genre labels and larger datasets to analyze.

The recent advent of LLM technologies in generative AI allows for future research to focus on and potentially differentiate between music production and lyrics generation, revealing possible heterogeneity in how AI is used as a tool for music creation or as a creator itself.

6.4 Final remarks

The introduction of AI in the music industry represents an important moment in the economics of culture - one that possibly mirrors the disruptive force of digital copying and streaming. By using a time-series intervention to analyze the phenomenon of AI in the supply of music releases, this thesis provides preliminary quantitative evidence that AI indeed has an influence on the global supply of recorded music.

Among its empirical contributions, this work underlines the possibility for further research into the topic of artificial intelligence in the music industry, showing preliminary findings of how emerging technologies can transform creative industries. With an abrupt evolution of AI technology, a proper analysis seems critical to understand the cultural and economic impact, allowing for informed practices in the context of policy and practice in the music sector.

References

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics, 40*(S1), S293–S340. https://doi.org/10.1086/718327

Adler, M. (1985). Stardom and talent. *American Economic Review, 75*(1), 208–212. http://www.jstor.org/stable/1812714

Aguiar, L., & Waldfogel, J. (2018). Quality predictability and the welfare benefits from new products: Evidence from the digitization of recorded music. *Journal of Political Economy, 126*(2), 492–524.

Akst, D. (2013). What can we learn from past anxiety over automation? *The Wilson Quarterly, 37*(3), 66–78. https://www.wilsonquarterly.com/quarterly/summer-2014-where-have-all-the-jobs-gone/theres-much-learn-from-past-anxiety-over-automation

Amankwah-Amoah, J., Abdalla, S., Mogaji, E., Elbanna, A., & Dwivedi, Y. K. (2024). The impending disruption of creative industries by generative AI: Opportunities, challenges, and research agenda. *International Journal of Information Management, 72*, 102759. https://doi.org/10.1016/j.ijinfomgt.2024.102759

Anderson, C. (2006). *The Long Tail: Why the Future of Business Is Selling Less of More*. Hyperion.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives, 29*(3), 3–30. https://doi.org/10.1257/jep.29.3.3

Bekar, C. (2013). Copying technologies. In R. Towse & C. Handke (Eds.), *Handbook on the digital creative economy* (pp. 105–115). Edward Elgar Publishing.

Bounie, D., Eang, B., & Waelbroeck, P. (2010). Marché Internet et réseaux physiques : comparaison des ventes de livres en France. *Revue d'économie politique, 120*(1), 141–162.

Brynjolfsson, E., Li, D., & Raymond, L. R. (2023). Generative AI at work (NBER Working Paper No. 31161). National Bureau of Economic Research. https://doi.org/10.3386/w31161

Caves, R. E. (2000). *Creative industries: Contracts between art and commerce*. Harvard University Press.

Cheng, Y., & Jiang, H. (2022). Customer-brand relationship in the era of artificial intelligence: Understanding the role of chatbot marketing efforts. *Journal of Product & Brand Management, 31*(2), 252–263.

CISAC. (2024). *Strategy and AI: The case for protecting human creativity in the age of AI*. International Confederation of Societies of Authors and Composers. https://www.cisac.org/services/reports-and-research/cisacpmp-strategy-ai-study

Coelho, M. P., & Mendes, J. Z. (2019). Digital music and the "death of the long tail." *Journal of Business Research, 101*, 454–460.

Cook, T. D., Campbell, D. T., & Day, A. (1979). *Quasi-experimentation: Design & analysis issues for field settings* (Vol. 351). Houghton Mifflin.

Cui, Z., Demirer, M., Jaffe, S., Musolff, L., Peng, S., & Salz, T. (2025). The effects of generative AI on high-skilled work: Evidence from three field experiments with software developers. *SSRN*. https://doi.org/10.2139/ssrn.4945566

Culture Action Europe. (2024, November 25). AI code of practice: first draft and first copyright meeting. Culture Action Europe. https://cultureactioneurope.org/news/ai-code-of-practice-first-draft-and-first-copyright-meeting/

Dohmke, T., Iansiti, M., & Richards, G. (2023). Sea change in software development: Economic and productivity analysis of the AI-powered developer lifecycle [Preprint]. *arXiv*. https://arxiv.org/abs/2306.15033

Drott, E. (2020). Copyright, compensation, and commons in the music AI industry. *Creative Industries Journal, 14*(2), 190–207. https://doi.org/10.1080/17510694.2020.1839702

European Parliament. (2025, June 1). MEPs learn about challenges that AI poses for the culture and creative sectors. https://www.europarl.europa.eu/news/en/press-room/20250601IPR28680/meps-learn-about-challenges-that-ai-poses-for-the-culture-and-creative-sectors

European Writers Council. (2025, March 28). Joint statement on the third draft code of practice. https://europeanwriterscouncil.eu/wp-content/uploads/2025/04/Joint-statement-on-the-Third-Draft-Code-of-Practice-28-March-2025-updated-v-07042025-002.pdf

Handke, C. (2012). Digital copying and the supply of sound recordings. *Information Economics and Policy, 24*(1), 15–29.

Hari, R. (2025, May 18). Klarna's AI replaced 700 workers— the fintech CEO wants humans back $40B fall. *Mint*. Retrieved from https://www.livemint.com/companies/news/klarnas-ai-replaced-700-workers-now-the-fintech-ceo-wants-humans-back-after-40b-fall-11747573937564.html

Henry, A., Wiratama, V., Afilipoaie, A., Ranaivoson, H., & Arrivé, E. (2024). Impacts of AI on music consumption and fairness. *Emerging Media, 2*(3), 382–396. https://doi.org/10.1177/27523543241269047

Hoffmann, M., Boysel, S., Nagle, F., Peng, S., & Xu, K. (2024). Generative AI and the nature of work (Working Paper No. 25-021). Harvard Business School. https://hdl.handle.net/10419/308375

IFPI. (2025). *IFPI Global Music Report 2025*. International Federation of the Phonographic Industry. https://globalmusicreport.ifpi.org/

Kretschmer, M., Klimis, G. M., & Wallis, R. (2001). Music in electronic markets: An empirical study. *New Media & Society, 3*(4), 417–441. https://doi.org/10.1177/14614440122226164

Li, S. (2025). The impact of AI-driven music production software on the economics of the music industry. *Information Development*. Advance online publication. https://doi.org/10.1177/0266666924131217

Maroutsis, I. (2024, December 20). Creators call for action on the impact of AI on Europe's creative communities. *Creatives Unite*. https://creativesunite.eu/article/creators-call-for-action-on-the-impact-of-ai-on-europe-s-creative-communities/

MusicBrainz Foundation. (n.d.-a). MusicBrainz. Retrieved May 20, 2025, from https://musicbrainz.org

MusicBrainz Foundation. (n.d.-b). MusicBrainz Wiki. Retrieved May 20, 2025, from https://wiki.musicbrainz.org

MusicBrainz Foundation. (n.d.-c). Statistics. Retrieved May 20, 2025, from https://musicbrainz.org/statistics

Landes, W. M. (2002). Copyright, borrowed images, and appropriation art: An economic approach. In R. Towse (Ed.), *Copyright in the cultural industries* (pp. 9–30). Edward Elgar Publishing.

Liebowitz, S. J. (2006). Creative destruction or just plain destruction? *Journal of Law and Economics, 49*(1), 1–28.

Liebowitz, S. J. (2008). Research note: Testing file-sharing's impact by examining record sales in cities. *Management Science, 54*(4), 852–859.

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science, 381*(6654), 187–192.

Oberholzer-Gee, F., & Strumpf, K. (2010). File sharing and copyright. In *Innovation Policy and the Economy* (Vol. 10, No. 1, pp. 19–55). University of Chicago Press.

Pan, J., Ferrer, C. C., McGuinness, K., O'Connor, N. E., Torres, J., Sayrol, E., & Giro-i-Nieto, X. (2017). SalGAN: Visual saliency prediction with generative adversarial networks [Preprint]. *arXiv*. https://arxiv.org/abs/1701.01081

Peng, S., Kalliamvakou, E., Cihon, P., & Demirer, M. (2023). The impact of AI on developer productivity: Evidence from GitHub Copilot [Preprint]. *arXiv*. https://arxiv.org/abs/2302.06590

Peters, J. (2025, April 28). Duolingo will replace contract workers with AI. *The Verge*. Retrieved from https://www.theverge.com/news/657594/duolingo-ai-first-replace-contract-workers

Potter Clarkson LLP. (n.d.). What data is used to train an AI, where does it come from, and who owns it? *Potter Clarkson.* Retrieved June 9, 2025, from https://www.potterclarkson.com/insights/what-data-is-used-to-train-an-ai-where-does-it-come-from-and-who-owns-it/

Raj, M., & Seamans, R. (2018). Artificial intelligence, labor, productivity, and the need for firm-level data. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda* (pp. 553–565). University of Chicago Press.

Rechardt, L. (2025, April 23). IFPI looks at a decade of digital transformation in the music industry. *WIPO Magazine*. https://www.wipo.int/web/wipo-magazine/articles/ifpi-looks-at-a-decade-of-digital-transformation-in-the-music-industry-73661

Resnikoff, P. (2016, August 3). Nearly two-thirds of all music sales come from just three major labels. *Digital Music News*. https://www.digitalmusicnews.com/2016/08/03/two-thirds-music-sales-come-three-major-labels/

Rob, R., & Waldfogel, J. (2006). Piracy on the high C's: Music downloading, sales displacement, and social welfare in a sample of college students. *Journal of Law and Economics, 49*(1), 29–62.

Rob, R., & Waldfogel, J. (2007). Piracy on the silver screen. *Journal of Industrial Economics, 55*(3), 379–395.

Robins-Early, N. (2024, April 2). Musicians demand protection against AI. *The Guardian*. Retrieved from https://www.theguardian.com/technology/2024/apr/02/musicians-demand-protection-against-ai

Rosen, S. (1981). The economics of superstars. *American Economic Review, 71*(5), 845–858.

Sheskin, D. J. (2003). *Handbook of parametric and nonparametric statistical procedures*. Chapman & Hall/CRC.

Society of Audiovisual Authors. (2024). *2024 – Artificial intelligence*. https://www.saa-authors.eu/en/pages/903-2024---artificial-intelligence

Strachan, I. (2013). Digitization and recorded music sales: Whither the 'long tail'? [Preprint]. *Social Science Research Network*. https://doi.org/10.2139/ssrn.2287193

Tigre Moura, F., & Maw, C. (2021). Artificial intelligence became Beethoven: How do listeners and music professionals perceive artificially composed music? *Journal of Consumer Marketing, 38*(2), 137–146. https://doi.org/10.1108/JCM-02-2020-3671

Tryon, W. W. (1982). A simplified time-series analysis for evaluating treatment interventions. *Journal of Applied Behavior Analysis, 15*(3), 423–429.

Varian, H. R. (2005). Copying and copyright. *Journal of Economic Perspectives, 19*(2), 121–138. https://doi.org/10.1257/0895330054048768

Young, L. C. (1941). On randomness in ordered sequences. *Annals of Mathematical Statistics, 12*(3), 293–300.

Zhou, E., & Lee, D. (2024). Generative artificial intelligence, human creativity, and art. *PNAS Nexus, 3*(3), pgae052. https://doi.org/10.1093/pnasnexus/pgae052

Appendix A

The global list of releases per year from 2000 to 2024

The raw data extracted from MusicBrainz for each individual release according to date was grouped into a group of releases counted annually (see Table A1).

Table A1

The global list of releases per year from 2000 to 2024

Year	count
2000	69,386
2001	72,904
2002	74,145
2003	79,258
2004	83,465
2005	90,265
2006	96,642
2007	99,554
2008	103,147
2009	106,563
2010	109,876
2011	114,844
2012	125,179
2013	129,032
2014	131,980

2015	137,250
2016	144,909
2017	151,942
2018	160,203
2019	170,590
2020	194,999
2021	186,751
2022	175,454
2023	168,807
2024	146,218

Appendix B

The yearly dates of releases of AI music production programs

However, despite these opportunities, the widespread integration of such tools is relatively recent, with the first music production AI-powered tools emerging in 2016. The full list of dates years for the introduction of each AI music production program ranges from 2016 to 2022 (see Table B1).

Table B1

The yearly dates of releases of AI music production programs

Tool	Category	Release date
iZotope Ozone	Automated Mastering	2018
LALAL.AI	Stem Separation	2020
BandLab SongStarter	Composition	2020
AIVA	Composition	2016
AWS DeepComposer	Synthesizer	2019
Moises AI	Stem Separation	2021
Magenta Studio	Generative AI	2019
StemRoller	Stem Separation	2021
Boomy	Composition	2018
Soundraw	Composition	2020
Loudly	Composition	2019
Amadeus Topline	Composition	2021
Atlas	Sample Organization	2020

Playbeat	Sample Organization	2017
Neoverb	Reverb	2020
RX 10	Audio Repair	2022
Dreamtonics Synthesiser V	Generative AI	2022
Orb Producer Suite	Generative AI	2019
Magenta (Project)	Generative AI	2016
MuseNet	Generative AI	2019
Jukebox	Generative AI	2020