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COORDINATOR Prof. Emidia Vagnoni

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Candidate

Supervisor

Dott. Rossi Luca

Prof. Magnani Marco

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Abstract

The proliferation of digital platforms has transformed economic behaviour, reshaping traditional markets and creating new avenues for interaction. Accelerated by the COVID-19 pandemic, reliance on digital solutions has intensified across sectors. Characterized by multisided markets, network effects, and scalability, these platforms have disrupted industries, altered consumer behaviour, and raised regulatory and ethical concerns. This thesis examines shifts in economic and societal behaviour induced by digital platforms, focusing on three interconnected domains: strategic voting, political consumerism, and user engagement in online marketplaces. Chapter 1 explores strategic voting in large-scale (televote) and small-scale (jury) elections within a positional voting system, using Eurovision and Spotify data. Findings reveal that strategic voting occurs to varying degrees in both televote and juries, with contest-generated data carrying more weight than Spotify data. This analysis underscores the prevalence of strategic voting and offers insights into voter behaviour, with broader implications for political and corporate governance. These findings provide important context for understanding the nuances of voting behaviour. Chapter 2 examines the impact of Justice Brett Kavanaugh's appointment to the US Supreme Court on music consumption patterns. Using Spotify streaming data, the study tests whether this political event influenced consumer behaviour, particularly boosting consumption of music by female artists. A difference-in-differences analysis indicates a 16% increase in consumption for female performers compared to males. Lyrical analysis further shows that songs addressing sexism and female empowerment grew in popularity during this period. The study contextualizes these shifts within broader trends. Chapter 3 investigates user behaviour in online second-hand marketplaces, focusing on the clothing sector. The study assesses how visual elements in product listings affect sales and pricing strategies. The key factor analysed is the subject type (clothing alone, real person, catalogue image, or professional model) and its impact on listing prices, sale likelihood, and time to sale. Regression analysis incorporating user experience, product reviews, and descriptions highlights the significance of visual presentation alongside reputation. Findings reveal that personal images, despite privacy concerns, can lead to higher prices or faster sales, varying by apparel category.

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Introduction

The rapid growth of digital platforms has profoundly changed many aspects of economic behaviour. Digital technologies have transformed traditional markets and opened up new opportunities for economic interactions, bridging gaps that previously limited access to goods, services, and information. They have shaped voter decisions through online campaigns and social media, offering targeted content and unprecedented access to political discourse. At the same time, they have influenced consumer habits through e-commerce and digital media, where personalized recommendations and instant access to products redefine how people shop and consume.

Furthermore, digital platforms have reshaped the functioning of shopping, especially with the growth of the sharing economy. A prime example is eBay, an online marketplace founded in 1995, which has established a decentralized system where individuals can engage as both buyers and sellers. eBay operates on a business-to-consumer (B2C) and consumer-to-consumer (C2C) business model, providing an online arena for buyers and sellers to interact. This innovation has enhanced market efficiency by offering greater accessibility and flexibility for participants, while also disrupting traditional business models. The rise of platforms like eBay has prompted changes in regulatory approaches and raised important questions about competition, fairness, and sustainability in the evolving economic landscape.

As digital platforms continue to advance, their influence on economic and social behaviour becomes increasingly significant. They provide opportunities for innovation and growth, but they also present challenges related to equity, transparency, and governance. Understanding and adapting to these changes is essential for harnessing the potential of digital platforms while mitigating their risks.

The onset of the COVID-19 pandemic further accelerated the digitization of many fields. With lockdowns and social distancing measures in place, both consumers and businesses¹

¹See e.g. McKinsey & Company Survey, *How COVID-19 has pushed companies over the technology tipping*

were compelled to adopt digital solutions at an unprecedented rate. This shift not only amplified existing digital trends but also introduced new behaviours and practices likely to have lasting impacts on economic activities. For instance, the increased reliance on online platforms for work², education, and social interaction³ has highlighted the critical role of digital technologies in maintaining economic and social continuity during crises.

Moreover, social media platforms have dramatically increased the speed and scope of information dissemination, reshaping how individuals and organizations engage with economic and social events. Real-time communication through platforms like Twitter, Instagram, and Facebook enables the rapid exchange of information, opinions, and news, influencing political decisions, consumer preferences, and even market outcomes. This fast-paced exchange of information is particularly important in times of crisis, where accurate and timely communication can be crucial for decision-making. However, it also poses challenges, as misinformation can spread just as rapidly, complicating efforts to ensure that reliable information guides economic and social responses. (Cinelli, Quattrocioni, Galeazzi, Valensise, Brugnoli, Schmidt, Zola, Zollo and Scala, 2020; Chen, Lerman and Ferrara, 2020)

Understanding societal and consumer behaviour transformations changes is essential for policymakers to regulate and increase fairness in digital platforms, for businesses, to adapt and succeed in a new digital economy. This thesis is driven by the need to shed a bit of light on how digital platforms are influencing economic and societal behaviour, with a focus on areas such as strategic voting, political consumerism, and user interactions in online marketplaces.

Digital platforms

Digital platforms are online spaces that bring together different groups of users to interact, exchange goods or services, or share information. For example, platforms like Amazon connect buyers looking for products with sellers who offer them, while Uber matches drivers with customers needing transport. These platforms thrive on network effects—meaning the more people use them, the more valuable they become. As more sellers

point—and transformed business forever, October 5, 2020

²See e.g. Brynjolfsson, Horton, Ozimek, Rock, Sharma and TuYe (2020)

³See OECD (2020)

join Amazon, buyers enjoy greater variety and competitive prices, while more drivers on Uber ensure quicker rides for customers.

From an economic standpoint, digital platforms act as middlemen, reducing transaction costs and reducing information asymmetries. Platforms such as Airbnb revolutionize the way travellers find accommodation by connecting them directly with hosts, while Vinted enables individuals to buy and sell second-hand clothing effortlessly. Spotify reshapes how we listen to music, and Facebook has changed the way we connect and share socially. Each of these platforms has transformed its industry by rethinking how users engage and transact with one another.⁴

Key features of digital platforms include several distinctive characteristics that set them apart from traditional business models. Firstly, they operate as **multi-sided markets**, serving multiple user groups simultaneously. For example, platforms connect buyers and sellers, content creators and consumers, or drivers and riders, facilitating interactions that benefit all parties involved. This structure enables platforms to create value by bringing together parties that might otherwise have difficulty finding each other.

Secondly, digital platforms benefit from **network effects**, where the utility that a user derives from the platform increases as more users join. Positive network effects can lead to rapid user base expansion and potentially result in market dominance. As the user base grows, the platform becomes more attractive, creating a virtuous cycle that accelerates growth and enhances competitiveness.

Thirdly, **scalability** is a fundamental characteristic of digital platforms. They can expand their operations quickly without a proportional increase in costs, owing to the low marginal cost of adding additional users or transactions. Once the platform infrastructure is in place, serving more users typically incurs minimal additional expenses. This scalability allows platforms to grow rapidly and efficiently adapt to increasing demand.

The economic impact of digital platforms is profound and multifaceted. They have **disrupted traditional industries** by introducing innovative business models that challenge established firms and alter competitive dynamics. In sectors such as retail (e.g. Amazon), transportation (e.g. Uber), hospitality (e.g. Airbnb), and media (e.g. Spotify), platforms have reshaped how services are delivered and consumed, often leading to significant shifts

⁴For a thorough inquiry into digital platforms, please see [Belleflamme and Peitz \(2015\)](#)

in market share and profitability.

Moreover, digital platforms have **created new markets**, exemplified by the rise of the gig economy (e.g. Deliveroo) and the sharing economy (e.g. Vinted). They have enabled the emergence of flexible work opportunities and better asset utilization, allowing individuals to monetize underused resources like spare rooms or personal vehicles. This development has opened up new income streams and transformed labour markets.

Consumer behaviour has also been significantly **altered** by digital platforms. The ease of access to goods and services, personalized recommendations, and user reviews have changed how consumers make purchasing decisions. The abundance of information and convenience offered by platforms encourages consumers to rely more on digital channels, affecting traditional retail models.

However, the rise of digital platforms has also **raised regulatory and ethical concerns**. Issues related to data privacy, market power, labour rights, and the spread of misinformation have emerged, prompting debates over appropriate regulatory frameworks. Policymakers are grappling with how to ensure that platforms operate fairly and transparently while fostering innovation and competition.

The COVID-19 pandemic magnified the role of digital platforms. With physical interactions curtailed, platforms became essential for maintaining economic and social activities. E-commerce platforms saw increased demand as consumers shifted to online shopping. Video conferencing tools became indispensable for remote work and education. Social media and streaming services provided avenues for entertainment and social connection.

This acceleration in digital adoption has several implications. There are **permanent behavioural shifts**, as some changes in consumer and business practices are likely to persist beyond the pandemic, solidifying the centrality of digital platforms in daily life. **Market concentration** has intensified, with leading platforms strengthening their market positions, raising concerns about competition and antitrust issues. Additionally, the increased reliance on digital platforms has highlighted the **digital divide**, emphasizing disparities in access to technology and the internet and underscoring the need for inclusive digital policies.

Strategic Voting

An important concept studied in this thesis is **strategic voting**. Strategic voting occurs when individuals cast their votes not solely based on their true preferences but rather to influence the outcome in a way that aligns more closely with their interests. Voters may support a less-preferred candidate who has a better chance of winning over a least-preferred one, aiming to prevent an undesirable outcome.

In this thesis, we explore strategic voting through the lens of the **Eurovision Song Contest**, a popular international music competition where countries vote for musical performances. The Eurovision context provides a **unique opportunity** to study strategic incentives for competing voters in a setting that is rather unique, featuring about 40 participants and having both juries and popular vote. By analysing voting patterns and preferences expressed during the contest, we can gain insights into how strategic considerations influence voter behaviour. The use of the **Spotify** platform in our analysis allows us to capture the true preferences of users during Eurovision. Spotify streaming data provides a rich source of information on actual music consumption behaviour, which may differ from the official voting results due to strategic voting. By comparing streaming data with voting outcomes, we can identify discrepancies between expressed preferences and actual behaviour.

While our study utilizes Eurovision as a case study, the results have broader applications in various **managerial fields**. Understanding strategic voting behaviour is crucial in corporate governance, particularly in company board elections where stakeholders may vote strategically to influence decisions or outcomes that affect organizational direction. The insights from our research can inform strategies for managing voting processes and stakeholder engagement in corporate settings.

Political Consumerism⁵

An essential concept in understanding the interplay between political events and consumer behaviour is **political consumerism**. Political consumerism refers to the deliberate choice of products and services based on political, ethical, or environmental considerations, where consumers use their purchasing power to express values and attempt to in-

⁵For a complete overview over Political Consumerism see [Boström, Micheletti and Oosterveer \(2019\)](#)

fluence corporate practices or societal norms. This form of consumer activism can manifest as either boycotting products from companies whose practices are deemed objectionable or *buycotting*, intentionally purchasing products to support companies or causes aligned with one's values. [Kam and Deichert \(2020\)](#) [Liaukonytė, Tuchman and Zhu \(2023\)](#)

In the context of this thesis, we explore political consumerism by examining the impact of Justice Brett Kavanaugh's appointment to the U.S. Supreme Court on music consumption patterns in the United States. The controversial nomination and subsequent confirmation hearings, which involved allegations of sexual misconduct, sparked significant public debate and activism, particularly around issues of gender equality and women's rights. We investigate whether this political event led to a shift in consumer behaviour, specifically an increase in the consumption of music performed by female artists.

By analysing streaming data from platforms such as **Spotify**, we aim to determine if there was a discernible change in listening habits that can be attributed to political consumerism. This approach allows us to capture real-time consumer preferences and behaviours in response to a political event. The findings have broader implications for understanding how digital platforms not only reflect but also facilitate expressions of political and social sentiments through consumption choices.

Thesis Contribution and Outline

Digital platforms play a central role in modern life, reshaping how people interact, consume, and engage in economic activities. This thesis explores the relationship between digital platforms and socio-economic behaviour across three distinct yet interconnected areas, all unified by a common thread, the digital platform itself. By investigating strategic voting, political consumerism, and user activity in online marketplaces, the research provides a structured analysis of how digital platforms influence and shape not only the actions but also the identities of economic participants, while simultaneously being shaped by them.

This thesis makes three key contributions:

Chapter 1 investigates strategic voting in both large-scale (televote) and small-scale (jury) elections within a positional voting system, specifically using the Borda count. This chapter uses the Eurovision Song Contest as a case study to explore how voters strategically allocate their votes to influence the outcome of the competition. We compare the voting patterns of the televote and the juries with streaming data of Spotify to identify discrepancies between expressed preferences and actual behaviour. The findings reveal that strategic voting manifests differently in televote and jury contexts, with contest-generated data exerting a significantly greater influence than Spotify data. These insights highlight the widespread presence of strategic voting in positional systems and offer valuable perspectives on voting patterns, suggesting that such behaviour could have important implications for the design of electoral systems, political accountability, and corporate governance by emphasizing the need for transparency and robustness in decision-making processes.

Chapter 2 examines how political tensions influence consumer behaviour, using Brett Kavanaugh's Supreme Court confirmation as a case study. By analysing Spotify's top 200 songs with a difference-in-differences approach, the study finds a substantial 16% increase in streams for female artists during the period spanning the Kavanaugh hearings. The findings indicate that heightened media coverage of gender issues during this politically charged time drove shifts in listening patterns. Robust to seasonal variations and platform-specific factors, these results shed light on political consumerism, illustrating how socio-

political events can shape consumption in unexpected domains like the music industry. This research highlights the interplay between political events and consumer behaviour, with important implications for addressing gender disparities and informing strategies in digital marketplaces.

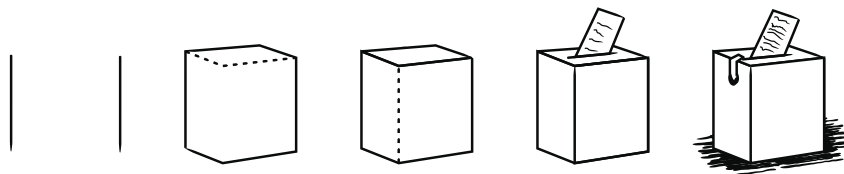
Chapter 3 focuses on user behaviour in online second-hand marketplaces, specifically within the second-hand clothing sector. The study examines how image presentation, in conjunction with seller attributes and product characteristics, influences sales performance. Using a dataset of over 1,000,000 listings posted in 2023 across five clothing categories from Tise.com, the research employs computer vision and machine learning techniques to analyse the interplay between visual presentation and seller appearance. It investigates the impact of different image types, such as photos featuring clothing alone, real persons, catalogue images, or professional models, on listing prices and the likelihood of a sale, while also accounting for user experience, product reviews, and descriptions. The findings reveal notable heterogeneity in the effectiveness of image types across product categories: for instance, real-person images boost sales for Dresses, whereas catalogue images perform better for Pants and Jackets. Furthermore, seller appearance exhibits a nuanced relationship with sales, with a slightly negative standalone effect but a positive interaction effect, suggesting that aligning seller profiles with product imagery can foster buyer trust and engagement. These findings offer users valuable guidance on selecting the most effective image type for their listings. For sellers, this translates into a higher likelihood of selling items, achieving higher prices, and potentially faster transactions. For platforms, the results can lead to increased commissions through higher prices and improved user privacy by revealing personal details only when necessary. Additionally, these strategies can increase user engagement and trust on the platform, fostering an environment that encourages more sales and attracts more users.

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Chapter 1

Country versus Music: Strategic Incentives for Competing Voters



1 Introduction

“My scheme is intended for only honest men”

Jean-Charles de Borda ([Black, 1958](#), p. 182)

The study of voting systems is fundamental to understanding collective decision-making processes. Traditional methods, such as the plurality rule, have long been criticized in social choice theory for their inability to capture the full spectrum of voter preferences. [Arrow \(1951\)](#) demonstrated that no voting system can simultaneously satisfy all desirable properties (e.g., unanimity, non-dictatorship, independence of irrelevant alternatives). Recent research further highlights the shortcomings of plurality voting: [Alós-Ferrer and Buckenmaier \(2021\)](#) argue that it exacerbates polarization by oversimplifying voter preferences and systematically favouring extreme outcomes. These insights underscore the importance of exploring alternative systems which better reflect voter intentions and reduce the risk of distorted outcomes. Examining these alternatives is crucial in the contexts where voting plays a central role, such as in political elections, organizational decision-making and cultural competitions.¹ Positional voting systems offer a promising alternative by incorporating voter preferences across multiple options and assigning distinct values based on rank order. One of the most widely known positional methods is the Borda Count (BC), a scoring rule that requires voters to provide complete rankings of all available alternatives. In the BC, each option receives a score corresponding to its rank, and these scores are aggregated to reflect collective preference intensities. Our analysis focuses on the BC because it provides a clear framework for studying strategic voting and preference aggregation in real-world settings.

Despite its advantages, the BC faces significant challenges, most notably its susceptibility to strategic manipulation. Although the method remedies some drawbacks of plurality voting, it violates Arrow’s axiom of independence of irrelevant alternatives. [Maskin](#)

This chapter is co-authored with Pietro Battiston, Marco Magnani and Dimitri Paolini

¹See [Maskin \(2025\)](#) among others.

(2025) contends that the standard axiom prevents the use of ordinal information to infer the intensity of individual preferences. To overcome this, he proposes a modified independence condition (MIIA) which requires that if individuals rank two alternatives in the same order and maintain the same number of alternatives between them, then the social ranking between those two alternatives remains unchanged. This relaxation allows the BC to capture subtle differences in preference intensities while still preventing vote splitting and spoilers. Moreover, since no voting rule is completely strategy proof, voters may misreport their preferences to influence the outcome, thereby distorting both the inputs and the collective decision (Dasgupta and Maskin, 2020). In fact, every social choice function, including the BC, is vulnerable to manipulation, especially in elections with more than two alternatives (Smith, 1999).

The consequences of these systemic flaws have become increasingly evident in the political arena. Heightened polarization in recent years has been fueled by unexpectedly close election outcomes on significant issues, such as the Brexit referendum in the UK and the 2016 US. Presidential election. Voters' reactions to these results have often been disheartening, as seen in the 2021 Capitol Hill rampage and the 2023 incidents at the Federal Parliament of Brasilia. These events exemplify the dramatic consequences of intense electoral competition and suggest that harsh polarization in the electorate may stem, at least in part, from the voting system itself. The failure of plurality systems to adequately represent nuanced voter preferences has likely contributed to these divisive outcomes. The BC remains mostly confined to specialized contexts such as elections in sparsely populated countries such as Nauru and Kiribati for national polls (with Slovenia using it for minority representation), as well as in entertainment contests such as the Eurovision Song Contest and in sports contexts, as the selection for the best football or baseball player. (Sy, Figuières, Rey-Valette, Howarth and De Wit, 2022; Laruelle, 2021).

Beyond politics, traditional voting systems pose significant challenges for decision-making within organizations. Corporate boards, management teams, and other groups often face decisions where single-choice voting fails to capture the full diversity of opinions and priorities (Laslier and Sanver, eds, 2010; Nurmi, 2002). Positional voting, by allowing members to express their preferences across multiple options, not only leads to outcomes that are more representative of the group but also reduces the potential for in-

ternal conflict and fosters more inclusive decisions (Laruelle and Valenciano, 2008; Sy et al., 2022). Moreover, by considering more than just a voter’s top preference, these voting rules are less likely to produce extreme outcomes. Adopting such methods enables selecting options acceptable to a large share of the electorate and can prevent systematic biases that push results toward knife-edge outcomes. This combination of features is particularly valuable in contexts where consensus-building is critical, such as in non-profit organizations, academic committees, or international negotiations.

The Eurovision Song Contest (ESC) provides a particularly interesting case study, which employs a voting mechanism similar to the BC. In the ESC, both juries and the public are prohibited from voting for their own country’s entry, creating a natural experiment for examining strategic behavior (i.e., when voters alter their votes to influence the final outcome). The contest’s hybrid scoring system, which combines rankings from national juries with televote, offers a unique opportunity to compare strategic behavior across small (jury) and large (public) electorates. To empirically investigate strategic manipulation, we leverage an integrated dataset that combines ESC voting records with Spotify streaming data (serving as a proxy for sincere voter preferences). This approach enables us to isolate strategic deviations and assess their impact on voting outcomes, thereby providing broader insights into the implications of strategic voting for electoral design.

The ESC competition is relevant for our analysis because each participating country votes for singers (or groups of singers) from all other countries. Importantly, the contest rules prohibit voting for one’s own country’s song, a constraint that likely leads voters to consider their own entry as the top choice, thus allowing us to analyse how participants strategically vote to benefit their country’s entry.

Furthermore, the ESC is well suited for analysing the role of information disclosure and coordination in strategic voting. Since 2008, the contest has included two sequential stages, semi-finals followed by a final. In the semi-final stage, voters have limited information about others’ preferences and are less likely to vote strategically. We can evaluate the extent of sincere voting by comparing semi-final votes with revealed preferences from Spotify national charts. In contrast, in the final stage, media disclosures about semi-final performances provide additional information that may encourage strategic voting. Comparing voting records between these stages allows us to assess the impact of enhanced

voter information on strategic manipulation. A second noteworthy feature of the ESC is its hybrid scoring system: the final ranking and the winning song are determined by a combination of votes from an expert committee and a popular jury via televote. This dual approach facilitates a comparison between the outcomes of large-scale elections and those of smaller, more focused electorates.

Our analysis reveals that strategic manipulation in positional voting systems is particularly pronounced in small electorates. In the ESC contest, strategic behaviour primarily influences the jury of music industry professionals, while the voting patterns of the popular jury remain largely consistent across contest stages. This observation aligns with expectations: in large-scale elections, the increased complexity and effort required for strategic voting tend to deter manipulation, whereas smaller, focused groups face lower costs and are more susceptible to such behaviour.

In light of these findings, we argue that positional voting can effectively aggregate nuanced voter preferences in large-scale elections. However, its adoption requires careful consideration of the information revealed at various stages and the potential for strategic manipulation to distort outcomes.

This paper is structured as follows. Section 2 reviews the relevant literature. Section 3 provides the necessary background, with subsection 3.1 describing the ESC voting rule and subsection 3.2 presenting an overview of strategic voting. Section 4 offers an overview of the data used. Section 5 presents the empirical model and the results, and Section 6 concludes.

2 Related Literature

Seminal contributions by [Gibbard \(1973\)](#) and [Satterthwaite \(1975\)](#) have shown that in any voting system, some voters may try to manipulate the outcome of the elections using strategic voting. This behaviour is the subject of a rich field of research in political economy, which seeks to understand its underlying logic (see, for example, [Myerson and Weber \(1993\)](#), [Cox \(1997\)](#), [Fey \(1997\)](#), [Myatt \(2007\)](#) and [Palfrey \(2023\)](#)).

Our paper contributes to the empirical literature, reviewed in the papers by [Pons and Tricaud \(2018\)](#) and [Eggers and Vivyan \(2020\)](#), whose focus is assessing the extent to which

voters behave strategically by considering strategic voting in a context different from majority rule. We analyse an election where a slightly modified version of the Borda rule is adopted. In particular, we focus on the ESC, a rare example of a large election where this voting rule is applied, and analyse how strategic voting impacts its outcomes for the first time.

Borda’s rule has induced voters to make strategic decisions instead of voting sincerely. For this reason several authors have studied strategic manipulation in this context, both from a theoretical point of view,² and from an empirical point of view, mostly using laboratory experiments.³ The results from laboratory experiments generally show that strategic behaviour emerges when voters recognize the potential to affect outcomes by misrepresenting their preferences. In particular, Forsythe et al. (1996) demonstrates how small group settings and repeated interactions lead to strategic voting. Kube and Puppe (2009) show that manipulation rates are significant when individuals are informed not only about other agents’ preferences but also about their actual votes. Bassi (2015) analyses strategic behaviour in three voting systems (plurality rule, approval voting, and the Borda count), showing that voters deviate from their sincere strategy the most in Borda count games without necessarily adopting the best response strategy.

Our empirical analysis confirms these tendencies, as we observe similar patterns of strategic voting among jurors in the Eurovision Song Contest. However, the scale and diversity of participants in our study introduce additional complexities, such as varying degrees of strategic sophistication, which may be less pronounced in the controlled environments of laboratory experiments.

Moreover, our analysis benefits from two key elements: access to detailed voting data that lets us track votes from the semi-finals and cross-reference them with Spotify data to gauge a song’s popularity outside the contest, and the ability to compare the outcomes of televote, with its large electorate, to those of the expert jury that determines the winner. This comparison enables us to assess whether strategic voting is more pronounced in high-turnout settings than in smaller electorates, as well as to analyse how varying levels of

²See for instance, Black (1976), Ludwin (1978), Saari (1990), Felsenthal (1996), Favardin, Lepelley and Serais (2002), Barbie, Puppe and Tasnádi (2006) and Lehtinen (2007).

³See Forsythe, Rietz, Myerson and Weber (1996), Kube and Puppe (2009), Bassi (2015), and Regenwetter and Grofman (1998).

participation influence voting strategies.

The behaviour of juries members is also investigated in several papers, which focus on the role played by different biases and strategic behaviour in determining the outcomes of the voting process. For instance, [Johnson and McCarthy \(2022\)](#) analyses different circumstances where committee members' votes are relevant, mainly in sports competitions and awards.

Many scholars have examined voting behaviour in the Eurovision Song Contest⁴, providing diverse explanations for both the public and jury voting that determines the contest winner. The explanations are directly linked to specific features of the songs and the artists⁵, or indirectly related to factors such as the order of performances ([Haan et al., 2005](#)) or the level of exposure of an artist or song to the public ([Verrier, 2012](#)). Other explanations highlight the presence of voting blocs between voters of different countries ([Fenn, Suleman, Efstathiou and Johnson, 2006](#); [Dekker, 2007](#)), or biases in voting behaviour primarily attributed to cultural and political issues, as well as geographic proximity⁶. However, none of these analyses explicitly consider the role of strategic voting, as we do in this paper. One exception is the paper by [Stockemer, Blais, Kostelka and Chhim \(2018\)](#), which is the closest to ours. These authors identify four types of voting behaviour: sincere, strategic, bandwagoning, and other behaviours. They use a survey on a small sample of respondents to check for discrepancies between preferences and declared votes. Their results indicate a limited use of strategic voting and more widespread adoption of bandwagoning and sincere voting. However, the existence of a significant fraction of voters whose behaviour remains unexplained and of a strategic effect in bandwagoning allows us to suppose that the role of strategy might be underestimated. Our results support this hypothesis, and despite relying on indirect evidence of strategic voting, it might offer a more accurate assessment of the phenomenon compared to the limited sample in [Stockemer et al. \(2018\)](#). The extensive data in our observation set enables us to analyse the issue more thoroughly.

⁴See [Budzinski and Pannicke \(2017\)](#) for an overview of this literature.

⁵See, for instance, [Haan, Dijkstra and Dijkstra \(2005\)](#), [Ginsburgh and Noury \(2008\)](#), [Spierdijk and Vellekoop \(2009\)](#), and [Budzinski and Pannicke \(2017\)](#).

⁶See [Haan et al. \(2005\)](#), [Blangiardo and Baio \(2014\)](#), and [Budzinski and Pannicke \(2017\)](#).

3 Background

3.1. The Eurovision Song Contest

The Eurovision Song Contest (ESC) is a rare example of large-scale elections where a version of the Borda Count (BC) is employed to aggregate voter preferences. This unique characteristic places it at the centre of our analysis, serving as our primary data source. Consequently, we need to dive into how the ESC operates.

The ESC is organized by the European Broadcasting Union (EBU), with approximately 40 countries participating. Traditionally, the host country for the ESC is the winner of the previous edition. According to the Rules of the ESC, each country's broadcaster "shall choose its performer through a national selection organized by each Participating Broadcaster. The national selection is organized under the sole responsibility of the Participating Broadcaster in question."

A maximum of 44 countries can participate in the ESC, with 26 countries competing in the final. In the final, there are six guaranteed places: one for the host country and one for each of the members of the "Big Five" (France, Germany, Spain, Italy and the United Kingdom). The songs must have a length equal to or less than 3 minutes. This rule applies only to the version performed during the live shows, and competing songs in a given year must not have been released commercially before the first day of September of the previous year to be eligible.

The votes of two distinct groups determine the scoring system of the ESC. The first group, the National Audiences, vote for their preferred songs in each participating country, excluding their country's entry; the song receiving the most votes is ranked first, the second-highest is ranked second, and so forth, down to the last song. The second group, the National Juries, consist of 5 members appointed by each participating country. These jury members rank the songs from their most to least favourite. Every song must receive a unique ranking, and abstentions are not permitted. Like the National Audiences, the juries cannot vote for the song from their own country and are not allowed to assign the same rank to multiple songs.

The contest entails two stages. The first stage consists of two semi-finals, which select

10 songs each, while the second stage, the Final, brings together the songs chosen in the semi-finals along with the songs of the “Big Five”. It is important to note that the semi-final results are not made public before the Final. In both the semi-finals and the Final, the score attributed by National Audiences in each country is determined as follows:

- 12 points to the song obtaining the best rank,
- 10 points to the song obtaining the second-best rank,
- 8 points to the song obtaining the third-best rank,
- 7 points to the next and down to 1 point for the song obtaining the tenth-best rank.

The scores attributed by National Juries are calculated in the same way.

The voting system described above is currently adopted in the ESC, but different systems were adopted in the past. Since 2004, the organizing committee has introduced several changes in the semi-final structure, voting methods, and point system. A better view of how it changed over the years can be seen in Table A.10. From 2004 to 2007, the event employed a single semi-final round where the outcome was determined solely by televote. This period marked the beginning of a more interactive approach, engaging the audience in the decision-making process.

In 2008, a significant shift occurred with the introduction of two semi-finals, diversifying the selection process. This year also marked the first instance of jury involvement, though limited, with the jury selecting the 10th qualified song, signalling a move toward a more balanced approach between audience preferences and expert opinions. Despite this, the final vote remained entirely dependent on televote.

The period from 2009 to 2015 saw the continuation of the two semi-final structures with a primary reliance on televote, but the final voting method transitioned to a 50/50 split between televote and jury voting. This period was significant for its approach to aggregated results, blending public opinion with expert judgment in the final decision. A further evolution was observed from 2016 to 2022. During these years, both the semi-final and final rounds adopted the 50/50 split between televote and jury voting, and a dual set of points was introduced, reflecting a more nuanced approach to scoring. The separate

presentation of televote and jury results added a layer of transparency and complexity to the scoring process.

From 2023, the event has retained the two-set point system and the 50/50 split in the final voting. However, a significant change was made to the semi-final voting, which reverted to a televote-only system. This change suggests a dynamic balancing act between audience engagement and expert judgment, continually adapting to the evolving context of the event.

These changes produced different data series used in our empirical analysis described in Section 4.

3.2. Strategic Voting

Consider an example of Borda elections where four voters and four alternatives are denoted with a letter from A to D. In this setting, the alternative ranked 4th by a voter receives 1 point, the alternative ranked 3rd receives 2 points, the alternative in the 2nd place receives 3 points, and the most preferred alternative receives 4 points.

The table below reports the distribution of voter preferences in the electorate.

Voter 1	Voter 2	Voter 3	Voter 4
A	B	C	D
B	A	A	B
C	C	D	A
D	D	B	C

If voters vote sincerely, the following results are obtained:

$$A \text{ Points } 4 + 3 + 3 + 2 = 12$$

$$B \text{ Points } 3 + 4 + 1 + 3 = 11$$

$$C \text{ Points } 2 + 2 + 4 + 1 = 9$$

$$D \text{ Points } 1 + 1 + 2 + 4 = 8$$

and alternative A should prevail.

However, people may not cast their votes according to preferences and choose to vote strategically instead. This occurs when voters want to maximize expected utility. In this case, a voter’s payoff is influenced by her vote only if it changes the election’s winner. Therefore, each voter must estimate the probability that any given pair of alternatives is in a sufficiently close race for first place. By casting her ballot, the winning alternative switches from one to the other (Myerson and Weber, 1993).

In the previous example, the race between alternatives A and B is very close. Voter 2 is positively likely to be pivotal in the election outcome if the remaining voters vote sincerely. Consequently, if Voter 2 maximizes expected utility, she votes strategically, ranking in the last position alternative A, the strongest competitor to her most preferred alternative, i.e. B. In this way, the score of A decreases to 10 and alternative B prevails in the election. Note that in the ESC context that we study, the rule adopted is not exactly a Borda rule: as described in Section 3.1, points are assigned based each voter’s ranking, but with a specific distribution which somehow resembles the related *Dowdall system* (Fraenkel and Grofman, 2014) in that, compared to the Borda rule, it favours candidates who often rank in the top positions of individual rankings.

The manipulability of the Borda rule is not a novelty, Borda himself, when the rule he had proposed was accused of not being robust to strategic behaviour, excused it by candidly admitting it was meant for “honest men”. More generally, by Gibbard’s theorem (Gibbard, 1973), any non-dictatorial social choice rule will be prone to strategic voting. However, the empirical setting we study, the Eurovision Song Contest (ESC), presents one feature that makes it of specific interest: a clear association between voters and candidates, in that each participating country has a set of voters (which includes both the popular vote and a jury) *and* a song competing. Hence, there is an obvious expectation that voters from a given country might want to favour the song from their own country. Precisely to counteract this obvious bias, the rules dictate that any country’s voters cannot vote for that country’s song. However, as will be shown, this is far from neutralizing opportunities for strategic voting. Indeed, voters are forbidden from explicitly supporting their presumably preferred option, but they have plenty of chances to disadvantage rival options. In principle, *all* options rival one’s preferred song. However, to the extent that the final position (and not the number of points, be it absolute or relative to participants) determines the

success of a song, the goal of a strategic voter will be to disadvantage candidates that are *close* rivals, such that changing their points tally by a small amount will possibly result in them swapping positions with one's preferred option. Indeed, while in standard elections only the winning candidate ultimately attains a given position and the associated power or privilege, with the other candidates deriving no benefit regardless of their relative success, the dynamics in the ESC are different. In the ESC, it is highly probable that voters from a given country will favour their country's song to some extent *regardless* of its actual chances of winning. This inherent bias toward national entries introduces additional layers of strategic behaviour that are not present in typical electoral contexts. As a result, analysing strategic voting in the ESC requires a distinct approach from the traditional frameworks in the literature. For instance, much of the existing research, such as that testing Duverger's Law ([Duverger, 1959](#)), has focused on plurality elections, where strategic voters are predicted to concentrate their support on the two strongest candidates, diverting votes from their most preferred option if its chances of winning are low. However, the ESC's structure, with multiple levels of competition and nuanced scoring systems, calls for an analysis that accounts for the complexity of voter motivations and the potential for strategic manipulation beyond simple vote concentration on front-runners.

As the literature on strategic voting shows, multiple equilibria emerge, posing a problem for strategic voters who must decide which equilibrium to focus on. A strategic coordination mechanism is required to coordinate voter actions (see [Granzier, Pons and Tricaud \(2023\)](#)). In this context, opinion polls ([Fey, 1997](#); [Myatt, 2007](#)) or past election outcomes ([Forsythe, Myerson, Rietz and Weber, 1993](#)) disclose the information needed for voters to converge on the candidates with the highest chances of winning the election and can serve as a coordination device. As already argued, the case of the ESC is particular because behind the voting structure, it is a contest, not an election, so even position improvements that do not result in getting the first position in the ranking are likely to be desirable and trigger strategic incentives somehow analogous to those characterized by Duverger's Law. Clearly, to the extent that the goal of voters is to have their nation's song to improve its positioning in the ranking, a song's main rivals are simply songs in the adjacent ranking positions, and more precisely, songs which are likely to obtain a similar number of points. Our investigation will precisely focus on votes cast by any voter for close songs, according

to some measure of distance, to the song from that voter's nation. Notice that, for a voter from country i , the most obvious incentive would be to penalize a song from a country j , which is just above in the rankings to favour a position change. At the same time, however, a voter from country j might anticipate this and penalize the song from country i precisely to avoid this. Hence, our main variable of interest is the *absolute* distance between points obtained by each song, we will still control whether a voter's song is above or below another.

If voters were entirely opportunistic, assigning votes *only* based on the chance to improve the position of their country's song, the mechanism would break down to a perfectly symmetric multiplayer discoordination game, where the only Nash equilibrium envisages all songs tied with the same points (as any song with more points would be immediately penalized). This is clearly not the case in the ESC, where, on the opposite, winning songs often gain significantly more points than runner-ups. We assume that voters' utilities include an element of honesty, by which they have sincere assessments of each song's merits, presumably correlated across voters, and suffer a utility loss by misstating them. That is, their utility will be of the form $u(r_i, \delta_0, \dots, \delta_{i-1}, \delta_{i+1}, \dots, \delta_N)$ where r_i is their country's song's ultimate position in the rankings, δ_j measures the difference between points awarded to song j by voter i and points the voter honestly thinks the song deserved, and u is decreasing in all its arguments (and symmetric in the last $N - 1$ arguments). Hence, the resulting votes will represent a compromise between trying to decrease r_i (strategic component) by at the same time limiting δ_j (taste for honesty).

Note that the game would be a zero-sum game if we limited the analysis to the r_i term, as each change of position implies a gain and a symmetric loss for the two involved countries/songs. It, however, ceases to be so when we consider that each increase of δ_j results in a net utility loss which is not compensated by any gain, as a possible decrease in r_i coincides with an increase in r_j for some other agent. Hence, the game is overall a social dilemma where agreeing to report preferences truthfully would maximize aggregated welfare. In fact, from the mathematical point of view, the model resembles several other social dilemmas found in the literature. For instance, if we limit to two players and assume that the two songs' quality is considered equal by both voters, our model can remind the one by [Lockard and Tullock \(2001\)](#). Note that absent any randomness, it would not be pos-

sible for the two voters to both apply strategic voting in Nash equilibrium: the one who does not win will rather report preferences truthfully (and a similar argument applies to the version with multiple voters and heterogeneous song quality). Thus, without mixed strategies, as in the continuous version of matching pennies, the model yields only corner solutions. However, when mixed strategies are allowed, the general game does not have a closed-form solution. For example, depending on the parameterization (specifically, on the functional form of the taste for honesty), the equilibrium best responses may either increase or decrease in response to the other agent’s strategic choices.

The circumstances described above disclose the information needed for coordination and may induce a change in voter behaviour resulting from strategic issues. The differences with the outcomes of the ESC final provide a measure of this change and the extent to which voters vote strategically. As a consequence, they are our main variables of interest. They are regressed on a set of explanatory variables: the distance between the scores (or the position in the ranking) obtained by the song of country j and the song of country i in the semi-final (or in the final). In the presence of strategic voting, in fact, the closer the race between the song of country i and the song of country j in the semi-final (or in the final), the more prominent the negative gap between the score (or the ranking) of the semi-final of the song of country i and the score obtained by this song from the National Audience or the National Jury of country j .

4 Data

We are considering three datasets.

Songs

This data that allows us to have a comprehensive overview of Eurovision songs from 2008 to 2023, encompassing a diverse range of musical characteristics and demographic data across 609 observations. The variables examined include technical aspects of music composition, such as danceability, energy, key, and tempo, as well as contextual features like the duration of songs, the percentage of female performers, and the size of performing groups. This dataset offers an extensive quantitative analysis, capturing the intricate nu-

ances of Eurovision songs. The variables are quantified in terms of mean and standard deviation, providing a statistical summary that reflects the diversity and complexity inherent in the musical and performance styles of the Eurovision entries. Table A.4 provides an overview of the Song Dataset.

Votes

The Votes Dataset contains data about votes and their breakdown, allowing us to comprehensively understand Eurovision votes from 2008 to 2023. In table A.3, we provide an excerpt of the 2022 final for the first country in alphabetical order. The columns display key voting details, including the rankings from the public televote and the professional jury, as well as the points awarded by both. They also contain a breakdown of the votes from each of the five jury members (J1 to J5). We provide in the appendix in table A.7 an example of the voting matrix from 2008 where no breakdowns were shared from the ESC.

In summary, for the empirical analysis of the scores, we divided the dataset into four dimensions. These dimensions capture varying levels of detail and are available for different time periods, as follows:

1. Aggregate scores awarded by audience and jury during the final for the years 1998-2023
2. Aggregate scores awarded by audience and jury during the final and the semi-finals for the years 2008-2023
3. Scores awarded by the audience during the final and the semifinals, for the years 2016-2023
4. Scores awarded by the jury during the final and the semifinals for the years 2016-2023

Spotify Charts

The dataset contains the Spotify platform's top 200 songs streaming per country. For each song, the dataset includes the track's rank, title, artist, and three additional metrics: the peak position the track has achieved, its previous rank, and its current streaming streak,

which appears to reflect the number of consecutive days the track has maintained its position within the chart. More importantly, the total number of streams for each track is provided, indicating the song’s overall popularity.

Overall, the dataset provides a structured glimpse into the music consumption trends within each country on each date, offering valuable insights for market analysis, artist popularity, and music streaming behaviours.

5 Empirical analysis

To detect if strategic voting takes place in the Eurovision Song Contest, we essentially estimate the following regression:

$$vote_{i,j,y} = \alpha + \beta distance_{i,j,y} + \gamma above_{i,j,y} + \delta distance_{i,j,y} \cdot above_{i,j,y} + \phi past_{i,j,y} \quad (1.1)$$

where the dependent variable $vote_{i,j,y}$ is the *relative* number of points that (voters of) country i award to the song of country j in year y , defined as the difference between actual points and the average points awarded by other countries to the song of country j .

The variable $distance_{i,j,y}$ is our main regressor of interest is calculated as following in equation 1.2.

$$distance_{i,j,y} = |points_{i,j,y} - \overline{points}_{j,y}| \quad (1.2)$$

It ideally captures the extent to which voters of country j perceive the song from country i as a close competitor in the ESC ranking. This is why voters should try to manipulate the elections and vote strategically: to change the ranking of the contest and favour their own country. To ensure that what it captures is not related to the *sign* of the difference between the points received by i and j , we also control for $above_{i,j,y}$, which takes value 1 if i received more points than j and 0 otherwise.

For the variable *distance*, we adopt two different approaches.

- *Internal metrics* We estimate the competitiveness of songs within the ESC using internal metrics based on the actual standing of a song in either the semifinal or final.

- *External metrics* We consider external indicators of a song’s chances of success, utilizing data from Spotify’s charts.

Given the above observations, strategic voting in our setting is signalled by a *positive sign for the coefficient β* . As the relative positions of the national song and the song of another competing country get closer, voters have more substantial incentives to award the competing song fewer points to reduce the probability of the national song being overcome in the final ranking. A low distance thus should result in fewer points.

In most specifications, we further control for a variable $past_{i,j,y}$, representing the average of points assigned by country i to country j in the 3 years before year y . We consider biases and clusters in voting patterns at the ESC by considering behavior in past editions.⁷

5.1. Internal measures

As mentioned above, different approaches can be conceived to measure the distance between two songs. We start by considering two definitions of $distance_{i,j,y}$ based on Eurovision votes data. Specifically, we consider the absolute value difference between the points received by the songs of the two countries (i) in the final rankings and (ii) in the semi-finals.

- Option (i) has two disadvantages. The first disadvantage is that it relies on the assumption that voters can forecast such final rankings — akin to assuming that players in a complex simultaneous game will play a Nash equilibrium. A second disadvantage is that the dependent variable $vote$ itself contributes to determining the rankings, so β can be affected by endogeneity issues.
- Option (ii) has the disadvantage that it reduces the sample size (the estimation can only be based on votes between country pairs competing in the same semifinals and reaching the final), but it solves the endogeneity problem and is guaranteed to be salient to voters in the final.

Table 1.1. Eurovision final–based *distance*

Dependent Variable:	Points						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	-0.028 (0.027)	0.021 (0.033)	-0.004 (0.038)	-0.360*** (0.038)	-0.443*** (0.066)	-0.381*** (0.099)	-0.505*** (0.086)
Above		-0.099*** (0.038)	-0.049 (0.054)	-0.052 (0.051)	-0.064 (0.087)	0.003 (0.132)	-0.132 (0.114)
Distance	0.446*** (0.160)	0.448*** (0.160)	0.658*** (0.225)	0.357* (0.215)	0.852*** (0.287)	0.994** (0.435)	0.711* (0.374)
Distance:Above			-0.422 (0.319)	-0.900*** (0.305)	-0.760* (0.407)	-1.031* (0.617)	-0.490 (0.531)
Past				0.146*** (0.005)	0.117*** (0.007)	0.090*** (0.010)	0.143*** (0.009)
Voters Years	Mean	Mean	Mean	Mean	All ≥ 2016	Jury ≥ 2016	Telev. ≥ 2016
Observations	9552	9552	9552	9552	9000	4500	4500
R^2	0.001	0.002	0.002	0.090	0.036	0.020	0.060
Adjusted R^2	0.001	0.001	0.001	0.089	0.035	0.019	0.059

Notes: Estimation of Equation (1.1) for different specifications of *vote*. For better readability, *distance* is expressed in thousands of points (while *vote* is expressed in points). The estimation covers the years 2008–2023, excluding 2020. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Option (i)

Column (1) in Table 1.1 shows the coefficients from estimates where the relative vote that voters of country i award to the song of country j in the ESC final in year y is regressed against the variable $distance_{i,j,y}$ defined as in definition (i). This relative vote is the (simple) mean between the points awarded by the jury and the points awarded by televoters; before 2016, we cannot split the scores between jury and televote. The coefficient β is positive and statistically significant. This reveals the presence of strategic voting because the points awarded by voters in country i to the song of country j get higher than total votes awarded in the final to country i and country j become more different. In other words, given a “domestic” song and a “foreign” song, if they are close to each other regarding the total number of points obtained in the final, domestic voters will penalize the foreign song because it is a strong rival of the domestic song. Domestic voters will assign more points to the foreign songs considered less of a rival. Column (2) shows the estimate results where

⁷Since a consistent stream of literature, reviewed by [Mantzaris, Rein and Hopkins \(2018\)](#), has identified systematic biases and clusters between countries we need to control for these factors.

we add the control variable “above”, which takes 1 if the song of country i ranks above the song of country j in the final, and 0 otherwise. The coefficient β remains strongly significant in this setting. The variable “above” is not significant as well as the interaction term “above · distance”.

This interaction becomes significant once we control for past behaviour of voters. Column (3) reports the results for the specification where we add the interaction term between *distance* and *above* as a control variable. In Column (4) we add as a control the mean of points attributed by country i to country j over the three previous Eurovision finals. This variable is meant to control for cross-vote patterns that persist over the years, which have been abundantly documented in the literature, and depend on cultural, political or simply geographical proximity and well-established voting blocs.⁸ In this framework, the coefficient associated with the variable *distance* remains significant and only slightly decreases. This decrease suggests that the strategic component of votes is more typically *aligned* with cross-country patterns than not. The interaction term displays a statistically significant negative coefficient. This result is somehow expected as it shows that voters are more inclined to award high scores to foreign songs which are not close competitors of the domestic song, i.e. to songs which are distant from the domestic song in the ranking, as long as their position is below the position of the domestic song.

If this is not the case and instead the foreign song is above and distant in the ranking from the domestic song, then voters award it scores which are below the average of the scores awarded by voters of other nationality. The net effect of the variable “distance” for songs which are higher in the ranking is in fact negative. The negative coefficient of the interaction term in fact exceeds in absolute value the positive coefficient associated to “distance”. Awarding lower scores to songs occupying higher positions in the ranking is a strategy to close the gap, with these strongest competitors. We call this effect the “catching-up effect”. The last three columns report the results for the model’s specifications, where votes awarded by the jury and televoters can be split. Data availability limits this analysis to the years from 2016 on.

In particular, Column (4) reports the results for a specification of the model analogous to the specification reported in Column (3), the only difference being the time spell con-

⁸See [Mantzaris et al. \(2018\)](#) for a review of these issues.

sidered. These results are a useful benchmark to interpret the content in the following two columns, respectively Column (5) and Column (6), where we report the results obtained, making use alternatively either of the votes awarded in the ESC final by the jury or of the votes awarded by televoters. The coefficient β in Column (4) remains statistically significant, preserves the positive sign and increases its magnitude. This provides further support to the hypothesis of strategic voting. The interaction term is again statistically significant and associated with a negative coefficient whose magnitude decreases. This suggests that the catching-up effect is less significant. If we consider separately the votes of televote and the votes of the jury, the presence of strategic behaviour is specially evident, as expected, in the case of the jury, where coordination costs are lower and information collection easier. The coefficient associated to “distance”, beyond being positive for both the jury and the televote, is in fact bigger in the former case. Moreover, the interaction term with the dummy “above” is only significant for the votes of the jury and has the usual negative sign that captures the catching-up effect.

Option (ii)

Table 1.2. Main results — *distance* based on Eurovision semifinal

Dependent Variable:	Points						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.238*** (0.061)	0.235*** (0.072)	0.239*** (0.085)	-0.344*** (0.083)	-0.332** (0.143)	0.031 (0.219)	-0.695*** (0.182)
Above		0.006 (0.080)	-0.002 (0.121)	0.043 (0.112)	-0.082 (0.190)	-0.380 (0.291)	0.216 (0.242)
Distance	2.595*** (0.819)	2.595*** (0.819)	2.519** (1.155)	2.557** (1.065)	3.254** (1.465)	2.496 (2.248)	4.013** (1.868)
Distance:Above			0.152 (1.639)	-1.873 (1.515)	-0.953 (2.078)	2.485 (3.189)	-4.390* (2.650)
Past				0.216*** (0.010)	0.194*** (0.014)	0.167*** (0.022)	0.221*** (0.018)
Voters Years	Mean	Mean	Mean	Mean	All ≥ 2016	Jury ≥ 2016	Telev. ≥ 2016
Observations	2700	2700	2700	2700	2520	1260	1260
R^2	0.004	0.004	0.004	0.153	0.072	0.051	0.109
Adjusted R^2	0.003	0.003	0.003	0.152	0.071	0.048	0.106

Notes: Equivalent of Table 1.1, except that *distance* is computed on the Eurovision semi-final rather than on the final. Years 2008–2023, except 2020. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Consider now the specification where the variable $distance_{i,j,y}$ is defined as in definition (ii). The results of the estimates are reported in Table 1.2, whose columns are symmetrical to the columns in Table 1.1. In Column (1), the relative vote that voters of country i award to the song of country j in the ESC final in year y is regressed against the distance between the songs of country i and country j in terms of the total points obtained in the semifinal of the ESC. The coefficient β remains positive and statistically significant. This result confirms the existence of strategic voting and highlights the fact that strategic behaviour is largely affected by the outcomes of the ESC semifinal. The magnitude of β is much larger than in previous estimates where the variable distance was based on the outcomes of the final and, importantly, increases from 0.446 to 2.595.

It is straightforward to interpret this result in light of the information revelation realized during the semifinals and crucial for shaping the strategy of voters. In the final, voters can rely on the information disclosed in the semifinals to elaborate a voting strategy. This information concerns, for instance, comments and news disclosed by media on the songs in the ESC. The outcomes of the semi-finals in fact are not made public. We can consider this stage of the ESC contest, which anticipates the final, as a mechanism that allows voters to coordinate their actions and direct their votes to weak competitors of the domestic song to enhance its chances of scaling up the ranking. The effect of the outcomes of the semifinals is particularly significant and summarizes most of the strategic elements that characterize voter behaviour. As evident from the results reported in Columns (2) to (7), the coefficients of the variables “above” and of the interaction term with “distance” are never statistically significant, with the sole exception of the specification where the votes of televote, where it is significant at 10%.

The information conveyed by voter past behaviour in the ESC is still relevant because the variable “past” always displays a positive and statistically significant coefficient. Nonetheless, once we control for issues like proximity and voting blocs, the strategic component captured by the coefficient β remains significant, and its magnitude is large. Taking Column (4) results as a reference point, which concerns the estimate incorporating both control variables “above”, the interaction term and “past” and are based on the longest available time series for ESC data, we observe a coefficient β equal to 2.557. This outcome suggests that, on average, voters in country i assign an additional 2.5 points to the song

of country j above the average score received by other countries for every 1,000 points of difference between the songs of country i and country j .

In terms of its impact on voting strategy, this implies that, for example, considering the figures from the ESC 2023 final (average distance between countries in ranking: 143.81 points, 25 countries competing in the final), 9.17 points out of the 58 allocated by each country to all songs except the domestic one in the contest are motivated by strategy. This amounts to 15.8% of the total, which is a non-negligible effect. As in the previous table, the last three columns display the results obtained when model specification separately considers the votes of the jury and televote. Column (4), which reports the outcome of the estimate where these votes are kept separate but analysed together, shows evidence in line with the results presented above, which confirms the importance of the variable “distance” as opposed to the variables “above” and the interaction term in capturing the strategic behaviour of voters. The variable “distance” displays a positive statistically significant coefficient whose magnitude is lower than in previous estimates, which uses data from 2008 to 2023 instead of considering only the period 2016-2023. Lastly, past votes matter in this setting, and the variable *past* has a statistically significant coefficient.

Comparing Column (6) and Column (7) shows that, contrary to the case where the variable “distance” is based on the results of the final, the jury behaves less strategically than voters of televote. In Column (6), which reports the results of the estimate concerning the jury votes, the coefficient *beta* remains positive but is not statistically significant, just as the coefficients of the variable “above” and of the interaction term. These parameters instead are significant in the case of televote with the exception of the coefficient of the dummy “above”, confirming previously observed characteristics of the strategic behaviour in the ESC.

A possible explanation for these results which are at odd with the theory, concerns the nature of the information which is revealed after the semifinal. This information in fact, is the only indirectly made available to televoters through the media. Jury members instead, are more likely to have access to superior information due to their role as insiders of the music market. As a consequence, while the strategic behaviour of televoters is largely driven by the performances of the national artist in the semifinals, the behaviour of jury members possibly responds more to different kind of information.

Table 1.3. Spotify-based *distance*

Dependent Variable:	Points				
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.458*** (0.111)	-0.237** (0.108)	-0.235*** (0.075)	-0.236*** (0.038)	-0.256*** (0.089)
Above	0.138 (0.139)	0.083 (0.140)	0.054 (0.093)	0.058 (0.049)	0.283** (0.124)
Distance	-0.017 (0.055)	-0.068 (0.091)	-0.012 (0.037)	0.001 (0.018)	0.111** (0.049)
Distance:Above	-0.084 (0.077)	-0.004 (0.128)	-0.055 (0.052)	-0.042* (0.025)	-0.193** (0.081)
Past	0.156*** (0.012)	0.068*** (0.010)	0.098*** (0.008)	0.061*** (0.004)	0.027** (0.012)
Years	≥ 2018	≥ 2018	≥ 2018	≥ 2018	≥ 2018
Distance	Charts	Charts	Charts	Charts	Charts
Delta	Semif.	Semif.	Semif.	Final	Final
Voters	Mean	Jury	Telev.	Mean	Mean
Observations	1592	1268	1578	5540	832
R^2	0.099	0.038	0.089	0.037	0.015
Adjusted R^2	0.097	0.035	0.087	0.037	0.010

Notes: Main results, with *distance* based on external measures: rankings in national Spotify charts for columns 1–3, prediction of success (points obtained in Eurovision) based on song features in columns 4–6. Years 2018–2023, except 2021. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5.2. External measures

The results above show that voters in the ESC engage in strategic voting, and shape their strategy on the information revealed during the contest, namely in the final or the semifinal. However, the results of the different stages of the ESC are not the only sources of information available to voters to coordinate their actions to improve the performance of the domestic song in the competition.

In this context, the most popular and possibly reliable source of information is the national charts of Spotify. The ranking in this chart reveals the preferences for the competing songs of voters in a specific country and, thus, the extent to which they consider this song a fierce competitor of the domestic song in the ESC.

We exploit Spotify data to answer different questions. A first question is whether the information coming from Spotify is relevant in affecting the strategic behaviour of voters. In particular, we can identify two situations where this could be the case. One situation in-

cludes the two semifinals. At this stage of the competition in fact, no information has been revealed within the ESC yet, and the only available information shall come from outside the contest. As a consequence, it is reasonable to expect that voters develop their strategies based on Spotify charts, which are easily available for all countries and cover a large subset of the songs in the ESC. A second situation when Spotify based information could be used is when voters must award a score to the songs of the so-called Big-Five (France, Germany, Italy, Spain and the UK), i.e. the countries which have direct access to the final of the ESC and do not participate in the semifinal stage. Also in this case in fact, the only available information about voter preferences must come from outside the contest. To answer this question, we need to measure the distance between songs in Spotify and to characterize a specific regressor “distance” to use in Equation (1.1).

This regressor originates from the daily Spotify charts of the most listened songs. We aggregate the position of each song on each national ranking into a single measure by assigning to each song several points equal to the number of songs *below* it in the national chart. We then add these points across countries. $distance_{i,j,y}$ is then defined as the difference, in points, between the points of song i and the points of song j . For this measure of the distance between different songs, data are available only from 2018 on. As a consequence, the number of observations significantly decreases. The results of the estimates where these measures are used to capture the effects of external information on the strategic behaviour of voters in the ESC final and semifinal are reported in Table 1.3. In this setting, we don’t include any measure of distance based on the competition within the ESC to focus on external measures. The evidence which emerges from this analysis is easily interpreted. External information is not relevant to the strategic behaviour of voters, no matter if we consider voting behaviours in the semifinal - Columns (1) to (3) - or in the final, Column (4). In this context, the only variable displaying a statistically significant coefficient is the variable “past” and shows that, in accordance with the results of other studies on voter behaviour in the ESC, if strategic voting is not explicitly considered, only past patterns matter. These findings strengthen the hypothesis that internal information mostly shapes voter strategies. The purpose of strategic voting is to improve the performance of the domestic song in the ESC, implying that the only salient information is the information generated by the specific dynamics observed in the contest, including those

deriving from voting blocs or the structure of the contest, as, countries distributions in the semifinals, or the ordering of the exhibitions in the final. All these issues are not captured by external information, which thus is less suit than internal information to shape voter strategies. It is worth noting that no differences emerge in this field between jury and televote.

This irrelevance result may be unexpected even when the semifinal results are considered, i.e., when no internal information has been generated yet. However, a possible explanation in this case is that the incentive to act strategically at this stage of the game is limited, given that the ranking of the semifinal can undergo substantial changes in the final. The only concern in this context, is to allow the domestic song to qualify for the final. This result is easily obtained for most countries, implying that the coordination effort required to vote strategically prevails over the expected benefits.

Interestingly enough, the only situation when external information matters is when we analyse the scores awarded to the Big Five. In this case the coefficient of “distance” is statistically significant and has the usual positive coefficient; analogously the interaction term displays a significant and negative coefficient which captures the catching-up effect. Lastly, the dummy “above” is also significant and with a positive sign, which shows that, on average, voters tend to penalize more foreign songs which are in a better position compared to the domestic song.

A second question concerning external information which is worth addressing is if the information coming from Spotify, i.e. information coming from a source which is external with respect to the ESC, is complementary to that that originated within the ESC, and somehow affects the strategic behaviour of voters.

We test this hypothesis by means of a set of estimates where internal and external measures of distance are jointly used as regressors. The results of these estimates are reported in Table 1.3.

Table 1.4 shows the estimation results employing these externally defined measures. We find that both internal and external distances are irrelevant when the outcomes of the semifinals are considered. This suggests that, as previously noted, that the strategic component in voter behaviour is quite limited during these stages of the contest. What matters in fact, is not the ranking of the semifinal itself, but the fact that the domestic song qual-

ifies for the final. When instead, the outcomes of the final are at a stake, we observe that internal distance remains significant and has the usual positive sign, when distance is measured based on the ranking of the final. The internal distance based on semifinal outcome instead is significant when televote is considered. In this context, i.e. when the variable distance is based on the semifinals, some complementarity between external and internal measures emerges as the interaction term between the dummy “above” (measured as) and external distance is considered. The associated coefficient is in fact, significant and negative and signals, as usual, the catching-up effect.

It is worth noting that the outcomes of televote show the biggest evidence of strategic behaviour, since, as it emerges from the results in Column (7), all the variables that captures strategic elements have statistically significant coefficients except the external distance. This seems to suggest that televoters are more prone to strategic voting than jurors which contradicts the standard prediction. *distance* has a mostly positive sign but is not statistically significant. This is interesting because it implies that the strategic voting component is emerging from the salience of competition and relative results inside Eurovision. It does not appear from other proxies of a song’s likelihood of winning or obtaining a suitable placement. In particular, this allows us to exclude the effect observed in Table 1.1 result from a spurious correlation between the tendency of different countries to candidate successful/unsuccessful songs to Eurovision and of voting for each other.

Table 1.4. Combination of internal and external distances

Dependent Variable:	Points									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	-0.399*** (0.142)	-0.313*** (0.100)	-0.159 (0.107)	-0.467*** (0.092)	-0.291*** (0.045)	-0.209*** (0.048)	-0.372*** (0.042)	-0.263** (0.105)	-0.273** (0.116)	-0.253*** (0.091)
Above	0.176 (0.187)	0.273** (0.132)	0.085 (0.141)	0.461*** (0.121)	0.063 (0.059)	0.015 (0.063)	0.111** (0.055)	0.140 (0.149)	0.226 (0.164)	0.054 (0.129)
External Distance	-0.014 (0.055)	0.054 (0.039)	0.072* (0.041)	0.036 (0.035)	-0.020 (0.020)	-0.029 (0.021)	-0.011 (0.018)	0.112** (0.057)	0.189*** (0.063)	0.035 (0.049)
External Distance:Above	-0.082 (0.078)	-0.144*** (0.055)	-0.117** (0.059)	-0.172*** (0.050)	-0.039 (0.028)	-0.017 (0.030)	-0.062** (0.026)	-0.282*** (0.094)	-0.291*** (0.103)	-0.273*** (0.081)
Past	0.157*** (0.012)	0.093*** (0.008)	0.086*** (0.009)	0.101*** (0.008)	0.060*** (0.004)	0.045*** (0.004)	0.075*** (0.004)	0.030** (0.012)	-0.008 (0.013)	0.069*** (0.010)
Internal Distance	-1.047 (1.478)	1.155 (1.041)	0.195 (1.116)	2.115** (0.955)	0.519** (0.215)	0.467** (0.228)	0.570*** (0.200)	-0.033 (0.466)	0.208 (0.514)	-0.274 (0.404)
Internal Distance:Above	-0.622 (2.091)	-1.028 (1.473)	0.782 (1.579)	-2.839** (1.352)	-0.047 (0.303)	0.075 (0.322)	-0.168 (0.283)	1.169* (0.673)	1.153 (0.741)	1.185** (0.583)
years	≥ 2018	≥ 2018	≥ 2018	≥ 2018	≥ 2018	≥ 2018	≥ 2018	≥ 2018	≥ 2018	≥ 2018
Internal Distance	Semif.	Semif.	Semif.	Semif.	Final	Final	Final	Final	Final	Final
External Distance	Charts	Charts	Charts	Charts	Charts	Charts	Charts	Charts	Charts	Charts
Dependent	Semif.	Final	Final	Final	Final	Final	Final	Final	Final	Final
Voters	Mean	Mean	Jury	Telev.	Mean	Jury	Telev.	Mean	Jury	Telev.
Subset								Big 5	Big 5	Big 5
Observations	1592	1592	1592	1592	5540	5540	5540	832	832	832
R ²	0.100	0.076	0.057	0.107	0.039	0.021	0.067	0.021	0.027	0.055
Adjusted R ²	0.097	0.073	0.053	0.103	0.038	0.020	0.066	0.014	0.020	0.048

This table reports the estimation of Equation (1.1) under various specifications. Coefficients are presented with standard errors in parentheses. “Above” denotes the indicator variable, and interaction terms (e.g., External Distance:Above, Internal Distance:Above) capture conditional effects. Years considered are ≥ 2018, with different subsets (e.g., Semifinal, Final, Jury, Televote, Big 5) as indicated. *p<0.1; **p<0.05; ***p<0.01.

6 Conclusions

This research examines strategic behaviour in positional voting, particularly in high-stakes elections. It considers the advantages of the Borda Count (BC) voting method, especially its ability to capture a broad spectrum of voter preferences while reducing the risk of extreme outcomes. The Eurovision Song Contest (ESC) serves as a useful case study, offering a real-world setting to observe how strategic voting unfolds throughout different stages of the competition.

The findings suggest that voters engage in strategic behaviour in different ways. Industry experts are more likely to manipulate their rankings compared to the public, likely because they have better access to information and a greater ability to coordinate. In contrast, strategic voting appears less common among the televote, where the complexity and effort required may act as a barrier. These patterns point to the role of information and coordination in shaping voting behaviour, reinforcing how positional voting systems aggregate preferences in large-scale elections.

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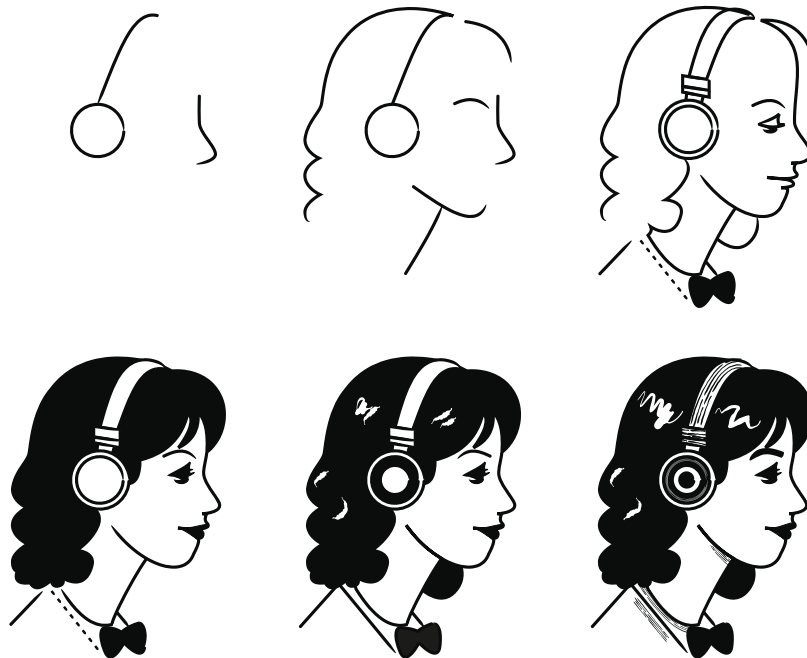
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Chapter 2

From Courtrooms to Charts: The Impact of Kavanaugh's Appointment on Music Consumption



1 Introduction

In recent years, gender inequality and sexual misconduct have come under increased public scrutiny, driven by social movements and high-profile events that have focused media attention on these issues. Despite their prominent exposure, the tangible impact of these events on everyday behaviour is still being actively studied ([Castle, Jenkins, Ortals, Poloni-Staudinger and Strachan, 2020](#); [Lins, Roth, Servaes and Tamayo, 2022](#); [Levy and Mattsson, 2023](#)). Does the increased media emphasis on gender inequality and women's rights function primarily as an awareness-raising tool, or does it also have the potential to affect changes in everyday behaviour?

To explore, we focus on a pivotal event that sparked public discourse on sexual misconduct: Brett Kavanaugh's appointment to the Supreme Court in October 2018. In this paper, we analyse how the increased media coverage of this event affected music consumption patterns. Specifically, we examine the impact of Kavanaugh's appointment on the streaming numbers of the top 200 songs in the US on Spotify. Using a difference-in-differences approach, we show an increase of at least 16% in the number of streams of songs by female artists, as opposed to male artists, within more than 60 days following Kavanaugh's appointment. An event-study analysis shows that songs by female and male artists followed comparable trends in terms of streaming numbers in the weeks before Brett Kavanaugh's appointment (October 8, 2018), with an increase in streams right after October 8 for songs performed by female artists. This increase in streaming is most pronounced in the first weeks after the appointment and persists for at least eight weeks into the winter holiday season. Our results are robust to the inclusion of artists, songs, and time fixed effects. Moreover, they retain their robustness regardless of the method used to define treated and control groups, particularly when considering collaborations between artists of the same

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gender or individual female and male artists. With a back-of-the-envelope calculation, we estimate that this shift in music consumption is equivalent to an increase of at least US\$120 in daily Spotify royalties for female artists associated with the increased streaming of their songs.

In this analysis, we show that significant events that draw media attention to issues of sexual misconduct and women's rights can influence everyday consumption decisions. This finding is consistent with previous research documenting the significant societal impact of the #MeToo movement. [Luo and Zhang \(2022\)](#) find that the hiring of female film writers by producers significantly increased following the Weinstein scandal in October 2017, especially for producers related to Harvey Weinstein. Additionally, [Levy and Mattsson \(2023\)](#) show a surge in the reporting of sexual crimes in countries with prominent #MeToo movements. More closely related to Kavanaugh's appointment, [Gelman \(2021\)](#) shows that US senators' communications changed after Kavanaugh's confirmation, with senators becoming more inclined to engage in partisan behaviour and get involved in partisan disputes. In comparison to these studies, our research explores a different aspect of behaviour and consumption that is not limited to specific groups (such as film producers, or senators) and examines an activity that is less critical but far more widespread than the reporting of sexual abuse.

The music industry provides a compelling context to study the impact of social movements on consumption patterns. First, changes in music consumption can be directly measured through the streaming of songs by different artists. Additionally, the gender of the artist is typically a distinct and easily identifiable aspect of his artistic output. Unlike other forms of consumption goods or artistic expression, such as movies, a song is performed by an individual or group of artists, leading listeners to commonly associate a song with the artists and their traits.

Our estimates capture the relative increase in streaming numbers for songs by female artists compared to their male counterparts. In doing so, our approach also accounts for potential negative effects on male artists. However, we believe that the magnitude of these negative effects is minimal. Throughout the analysis period, streaming numbers for male artists remained stable. In addition, our analysis did not find significant differences when comparing male artists' songs with similar characteristics to those of female artists and

may be more susceptible to being replaced by female artists' songs. Finally, the observed increase in streams for female artists' songs holds up even when we use songs by groups or multi-artist collaborations as a control group.

The data come from the US Spotify charts. While we cannot rigorously test the possibility that the platform may have promoted certain artists during this period, such promotion did not appear to occur through Spotify's most prominent "New Music Friday" playlist, which did not feature a higher number of female artists during our analysis period. Additionally, we can rule out seasonal effects or the presence of confounding effects related to the new entry of a few songs by top artists. Placebo analyses conducted in 2017 and 2019 show similar streaming patterns for male and female artists, with no notable changes over the same months. The robustness of our results is also confirmed when we restrict our analysis to artists outside the top five daily streams.

Finally, the music industry is particularly appealing for this study because we can analyse the lyrics of each song. This allows us to examine whether the impact is more pronounced for songs with sexist terms in their lyrics. When we focus on such songs, we observe an effect that is larger in magnitude and longer lasting, suggesting that sexist terms play a different role for female and male artists, and that media attention to gender issues had a specific impact on this subset of songs.

Our research contributes to the understanding of gender imbalances in the music industry. Previous studies have primarily focused on describing gender representation in the field (Smith, Choueiti, Pieper, Clark, Case and Villanueva, 2018; Epps-Darling, Cramer and Bouyer, 2020; Aguiar, Waldfogel and Waldfogel, 2021). In contrast, our work examines how these gender imbalances, particularly in terms of consumer preferences for different artists, are not static but can be influenced by external events. Given the significant political implications of the Kavanaugh appointment, our study also adds to the emerging literature on political consumerism and how politics affect consumer preferences.

Brett Kavanaugh's confirmation process was highly contentious, marked by allegations of sexual assault, intense political debate, and extensive media coverage.¹ The confirma-

¹According to Nielsen's data, the viewership for Brett Kavanaugh's testimony before the US Senate Judiciary Committee on September 27, 2018, exceeded 20 million people. For further reference, see: <https://apnews.com/article/caa510f21dcd4c569a4c8ea91f587a44>.

tion to the Supreme Court was finalized with a particularly narrow Senate vote of 50-48, one of the closest margins in American history for a Supreme Court nominee. His appointment shifted the ideological balance of the Court, as Kavanaugh is perceived to have a more conservative stance on various issues, including abortion. This shift was considered pivotal in the context of abortion rights, increasing the likelihood of the Supreme Court adopting positions less supportive of the precedent set by *Roe v. Wade*.²

Given the nature of Kavanaugh's accusations and his ideological leanings, our work shows that the heightened political polarization had an impact on consumer preferences, particularly regarding goods such as songs that are easily associated with the gender of artists. This is in line with the recent work by [Schoenmueller, Netzer and Stahl \(2023\)](#), which shows increased polarization in preferences and purchase decisions after the election of Donald Trump in 2016. In this case, the change in consumption did not regard brands or products that take a stance on a specific topic or endorse a political figure ([Hydock, Paharia and Blair, 2020](#); [Hambrick and Wowak, 2021](#); [Bondi, Burbano and Dell'Acqua, 2022](#); [Liaukonytė, Tuchman and Zhu, 2023](#)). Rather, it concerned products associated with a particular movement or ideology due to a product feature, irrespective of the ideology of the sellers or producers. In this respect, our work is akin to previous studies demonstrating the boycott of French products by American consumers during the dispute between France and the US over the Iraq War ([Chavis and Leslie, 2009](#); [Pandya and Venkatesan, 2016](#)).

Finally, our work contributes to the literature on the design of digital marketplaces and how gender imbalances affect these platforms. Platform design choices, including algorithms and featured content, have a significant impact on the popularity of products, such as songs in this context. These platforms must recognize and adapt to external factors and events that may exacerbate or mitigate existing imbalances. In our case, the political climate following Kavanaugh's confirmation provided a positive boost to female artists, thereby reducing gender imbalances.

²For more information, see: <https://www.bbc.com/news/world-us-canada-45774174> and <https://www.bostonglobe.com/news/politics/2018/07/11/how-judge-brett-kavanaugh-confirmation-could-affect-roe-wa-s1ZbShSQk6rcFfjrV6x1m0/story.html>.

2 Empirical Setting and Dataset

The data comes from Spotify’s publicly available charts and it contains daily snapshots from September 3, 2018, to December 23, 2018, about the top 200 songs in the US, ranked according to streaming numbers.³ The data includes metrics such as the number of days a song has appeared on the charts, its daily ranking (from 1, the highest, to 200, the lowest), and the number of streams. We enrich our dataset with additional information about songs and albums from Spotify’s public APIs. This approach allows us to obtain detailed features for each song. We also gathered copyright holder details, release dates, and other relevant information from Spotify. To determine artist gender, we employed a two-step approach. First, we use the MusicBrainz APIs to retrieve the gender of artists.⁴ Then, in case of missing information from MusicBrainz, we retrieve manually the artist’s gender using the artist Wikipedia’s page or the artist’s picture shown on Spotify.⁵ Doing so, we identify 57 unique songs performed by a female artist or a collaboration between two female artists, and 385 songs performed by a male artist or a collaboration between two male artists. These songs are performed by 164 unique artists, consisting of 37 female artists and 127 male artists. We also identify 189 songs performed by groups or collaborations of more than two artists.

In the remainder of this section, we explore the evolving dynamics of public discourse on sexual misconduct, with a particular focus on the appointment of Brett Kavanaugh to the Supreme Court. This high-profile event serves as a pivotal point in our study, as we examine its impact on music consumption patterns. We conclude the Section by presenting descriptive statistics.

³For more information, see: <https://charts.spotify.com>.

⁴MusicBrainz is an open music encyclopedia that collects and makes music metadata publicly available. See: <https://MusicBrainz.org/>.

⁵Solo artists are assigned a gender based on their self-identified gender. See Appendix Figures B.1 and B.2 for screenshots of MusicBrainz and Spotify artist webpages used to retrieve artists’ gender.

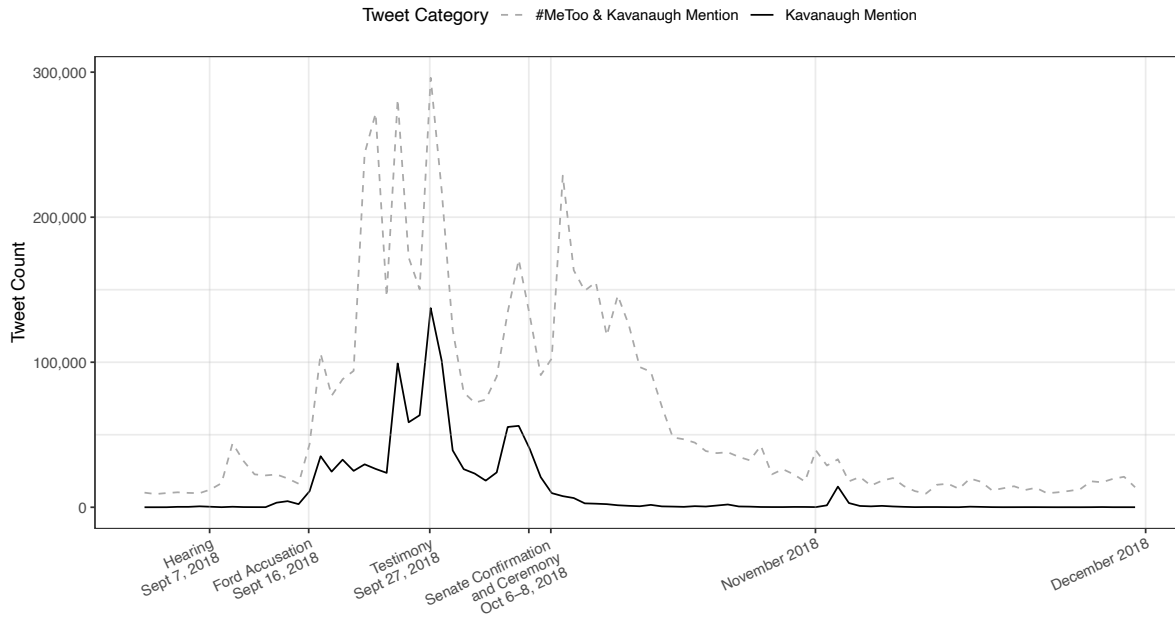


Figure 2.1. #MeToo and #Kavanaugh Tweet Counts Over Time

Notes: This figure shows the daily number of tweets containing the #MeToo hashtag (solid line) and the number of tweets containing the #MeToo and #Kavanaugh hashtags or mentioning the word “Kavanaugh” in the tweet (dotted line) from September 2018 to February 2019, as extracted from the public Harvard Dataverse (Maiorana, Morales Henry and Weintraub, 2023).

2.1. The Kavanaugh Appointment and Its Impact on Public Discourse on Sexual Misconduct

The appointment of Brett Kavanaugh to the Supreme Court represented a pivotal moment in the discourse about sexual misconduct, particularly within the context of the #MeToo movement. Originally sparked to combat sexual harassment and assault, this movement has emerged as a critical force in challenging entrenched societal norms and empowering survivors to voice their experiences.⁶ However, Kavanaugh’s nomination shifted the focus from the entertainment industry to the upper echelons of political power, highlighting the broader societal implications of these issues (Rhode, 2019, Grover, 2019).

An analysis of the use of the #MeToo hashtag from October 2017 to January 2020 (Appendix Figure B.3) reveals three notable spikes in public engagement. The first spike, in October 2017, coincided with Alyssa Milano’s endorsement of the #MeToo hashtag. A

⁶For an overview, see: https://en.wikipedia.org/wiki/MeToo_movement.

subsequent surge occurred on January 7, 2018, following Oprah Winfrey's speech at the Golden Globes.⁷ The spike with the longer span coincides with the period of Kavanaugh's nomination (September to October 2018). Figure 2.1, which narrows the focus to September 2018 to February 2019, shows how the spike in tweets associated with the #MeToo movement in the fall of 2018 is particularly related to Kavanaugh's nomination, as a significant portion of them include the hashtag #Kavanaugh or mention the word "Kavanaugh" in the tweet.

The sexual assault allegations against Kavanaugh during this period intensified media scrutiny and sparked widespread public discourse.⁸ These events marked a critical expansion of the movement's scope beyond the confines of the entertainment industry to address broader social and political concerns. This expansion is consistent with the findings of [Levy and Mattsson \(2023\)](#), which found that while the spike in Google searches about the #MeToo movement began in October 2017, media coverage of sexual assault spiked in the months leading up to Kavanaugh's confirmation.

Kavanaugh's nomination became a focal point in the debate on sexual misconduct, carrying major implications for gender politics in the United States. Jennifer Lawless, Commonwealth Professor of Politics at the University of Virginia, underscored the broader implications: "The stakes here go beyond our societal perceptions of women's roles to the future of *Roe v. Wade* and women's reproductive rights."⁹

Taking advantage of the heightened focus on gender-related policies during Kavanaugh's nomination to the Supreme Court, our study seeks to examine how increased public interest in specific issues might influence consumer behaviour, with a particular focus on music consumption patterns.

⁷See https://twitter.com/Alyssa_Milano/status/919659438700670976 and <https://www.nytimes.com/2018/01/07/movies/oprah-winfrey-golden-globes-speech-transcript.html> for more details.

⁸For detailed coverage of these allegations, see: <https://www.nytimes.com/2018/10/02/us/politics/kavanaugh-news-fbi-investigation.html>.

⁹This quote from Professor Lawless was reported in an article by Sabrina Siddiqui for The Guardian, cited in [Siddiqui \(2018\)](#). For an examination of the impact of Brett Kavanaugh's confirmation on *Roe v. Wade*, see <https://www.bostonglobe.com/news/politics/2018/07/11/how-judge-brett-kavanaugh-confirmation-could-affect-roe-wade/s1ZbShSQk6rcFfjrV6x1m0/story.html>.

2.2. Data Description

Our analysis spans from Monday, September 3, 2018, to Sunday, December 23, 2018. This timeframe was deliberately chosen to examine the impact of Brett Kavanaugh’s public appointment ceremony on October 7, 2018, while avoiding the variability often observed in summer chart movements. Seasonal trends in music consumption significantly influence chart dynamics, with the summer months experiencing shifts driven by changing listening habits and the annual push to produce a so-called “song of the summer”.¹⁰ Artists and record labels strategically aim to create such hits by emphasizing energetic tempos, catchy hooks, and feel-good themes that resonate with summer audiences. These seasonal influences introduce volatility into music charts, making it challenging to isolate external factors affecting music trends. By selecting a post-summer timeframe, our study minimizes these seasonal distortions, providing a more stable foundation for analysing chart performance during high-profile political events.

Table 2.1 presents summary statistics derived from the Spotify chart dataset during this period. Here, we compare songs by female and male artists, focusing on various aspects such as average song performance on Spotify, artist popularity, and song characteristics. In Appendix Table B.1, we perform a similar analysis, this time comparing songs by female artists with those by groups. The unit of observation remains at the song/daily snapshot level throughout our analysis.

Songs performed by female artists account for 2,120 observations in the daily top 200 charts, while those performed by male artists account for 14,103 observations. This is consistent with the findings by [Smith et al. \(2018\)](#), who show that of the top 600 songs in the Spotify billboards from 2012 to 2017, only 22.4% are performed by female artists, and only 12.3% are written by female artists. Appendix Figure B.4 provides a visual representation of the gender distribution in the charts from 2017 to 2020. A notable increase in the proportion of female artists in the charts starts after October 2018, and remained stable since then. Female artists generally experience a shorter chart duration, about 83 days less on average, which is a 50% difference compared to male artists. Despite the relatively lower

¹⁰A “song of the summer” is a track that achieves widespread cultural recognition, is frequently played across multiple platforms, and often becomes inescapable during the season.

Table 2.1. Summary Statistics - Songs by Female and Male Artists in US

	Female		Male		Difference	
	Mean	SD	Mean	SD	Δ	P-value
Charts						
Days on Chart	78	76	161	176	-83	0
Chart Rank	101	58	98	58	3	0.02
Week of Release	0.04	0.19	0.13	0.33	-0.09	0
Streams	449,715	386,390	439,051	288,533	10,664	0
Artists						
Artist Followers	51,544,874	40,983,042	24,882,703	26,019,201	26,662,171	0
Song Characteristics						
Song Duration (Seconds)	203	27	194	51	9	0
Is Explicit	0.32	0.46	0.81	0.39	-0.5	0
Major Record Label	0.72	0.45	0.5	0.5	0.22	0
Is Empowering	0.34	0.48	0	0.06	0.34	0
Is Sexist	0.18	0.38	0.61	0.49	-0.44	0
Is Single Release	0.56	0.5	0.2	0.4	0.36	0
Song Features						
Acousticness	0.3	0.3	0.25	0.26	0.06	0
Danceability	0.62	0.13	0.73	0.14	-0.11	0
Energy	0.58	0.17	0.58	0.15	0	0.7
Musical Mode	0.6	0.49	0.62	0.49	-0.02	0.09
Speechiness	0.08	0.06	0.16	0.12	-0.08	0
Tempo (BPM)	119.21	28.2	125.64	29.07	-6.42	0
Time Signature	3.9	0.3	3.97	0.22	-0.07	0
Valence	0.38	0.17	0.43	0.2	-0.05	0
Number of observations:	2,120		14,103		-11,983	

Notes: The table shows summary statistics about songs present in the Spotify top 200 us billboard between September 03, 2018 and December 23, 2018. Comparisons made between 57 (4) songs by female and 385 (164) songs from male artists. Gender identification based on publicly available data on MusicBrainz, Spotify, or Wikipedia.

representation of female artists compared to male artists, songs by female artists that make it into the top 200 charts receive, on average, approximately the same number of streams, and female artists typically have more than two times as many Spotify followers as their male counterparts.

Yet, only 15% of chart entries for female artists occur during the week of the song's release, in stark contrast to the 54% for male artists. This discrepancy may indicate different marketing strategies or release tactics employed by the music industry for male versus female artists. In line with this point, we observe some notable disparities between male and female artists in the proportion of songs associated with a major record label, that are single tracks, contain explicit lyrics, or lyrics with at least one sexist verse. To measure

the presence of sexism in lyrics, we use the BERTweet classification algorithm (Nguyen, Vu and Nguyen, 2020), which analyzes song content for offensive or derogatory language. The algorithm defines a term as sexist following the Explainable Detection of Online Sexism (EDOS) dataset (Kirk, Yin, Vidgen and Röttger, 2023).¹¹

Female artists have a higher frequency of major label affiliation, tend to release more singles, and their songs generally contain less explicit and sexist lyrics than their male counterparts. Finally, Spotify proposes a set of features to describe the sound and the rhythm of each song. In Appendix B, we provide a complete description of each feature following Spotify definitions. Some of these variables show statistically significant differences between male and female artists, with varying magnitudes and directions. For instance, female artists’ songs have lower danceability and tempo than male artists. These findings suggest that songs by female and male artists have different features and may attract audiences with different tastes.

3 Identification Strategy

We use a difference-in-differences design to measure the effect on music consumption of the increased interest in gender-related policies during Kavanaugh’s nomination to the Supreme Court. To do that, we compare the Spotify streams for songs by female and male artists over time. The main estimating equation is as follows:

$$\log(\text{streams}_{it}) = \theta_i + \gamma_t + \beta_1 \text{Female}_i \times \text{Post}_t + \beta_2 \mathbf{X}_{it} + \varepsilon_{it}, \quad (2.1)$$

where $\log(\text{streams}_{it})$ denotes the natural logarithm of the streaming count for song i at day t ; and θ_i and γ_t capture song-specific and day-specific fixed effects.¹² The variable Female_i is a dummy variable taking value 1 if song i is performed by a female artist or two female artists’ collaborations, and 0 if it is performed by a male artist or two male

¹¹For more information about the BERTweet classification algorithm and the EDOS dataset, see: <https://huggingface.co/NLP-LTU/distilbert-sexism-detector>.

¹²We use the International Standard Recording Code (ISRC) as a unique identifier for each song. This is necessary since a single song could have multiple Spotify IDs.

artists' collaborations. The variable Post_i is equal to 1 for dates after October 8, 2018, the day after the public ceremony of appointment at the White House of Brett Kavanaugh as Supreme Court Judge. We use this date as it marks the official conclusion of the nomination process. However, as illustrated in Figure 2.1, interest in the movement and the topic of sexual abuse had already started to rise a few days prior, suggesting that there might have been anticipation of media and public attention beginning a few days earlier. Finally, the set of controls, grouped in $\mathbf{X}_{it}$, includes factors such as whether song i was newly released that week or if it was present on the chart the day before.

The coefficient β_1 captures the effect of the increased interest in gender-related policies and sexual misconduct on the consumption of music performed by female artists. This is under the assumption that songs performed by male artists, serving as the control group, provide a suitable counterfactual for the dynamics of music streams after October 8, 2018. To test the absence of pre-trends between treated (songs by female artists) and control (songs by male artists) groups, we illustrate the evolution of $\log(\text{streams}_{it})$ over time with an event-study approach. We regress $\log(\text{streams}_{it})$ over the product between the dummy Female_i and a full set of dummy variables for each day from Monday, September 3, 2018, to Sunday, December 23, 2018. The model controls for song fixed effects, day fixed effects, and dummy variables indicating whether the song is already present on the chart the day before, and whether it is a new release of that week:

$$\log(\text{streams}_{it}) = \alpha_i + \rho_t + \sum_{\tau=\text{Sep1},3}^{\text{Dec23},6} \beta_\tau \text{Female}_i \times 1(t = \tau) + \varepsilon_{it}. \quad (2.2)$$

We present the results of the estimates of Equation 2.2 in Figure 2.2, where we plot the estimated β_τ from September 3, 2018, to December 23, 2019. The coefficients corresponding to days before October 8, 2018, are close to zero and do not exhibit a clear trend. Thus, the stream's dynamics for songs performed by female or male artists was similar before the appointment of Brett Kavanaugh as Supreme Court Judge. This finding supports the parallel trend assumption, which is necessary for our analysis. Instead, after October 8, 2018, the estimated β_τ s show a positive trend, meaning that the streams for songs by female artists increase relative to songs by male artists. The effect persists for more than 60 days and declines during the period of the Christmas holidays. In Appendix Figure B.5, we

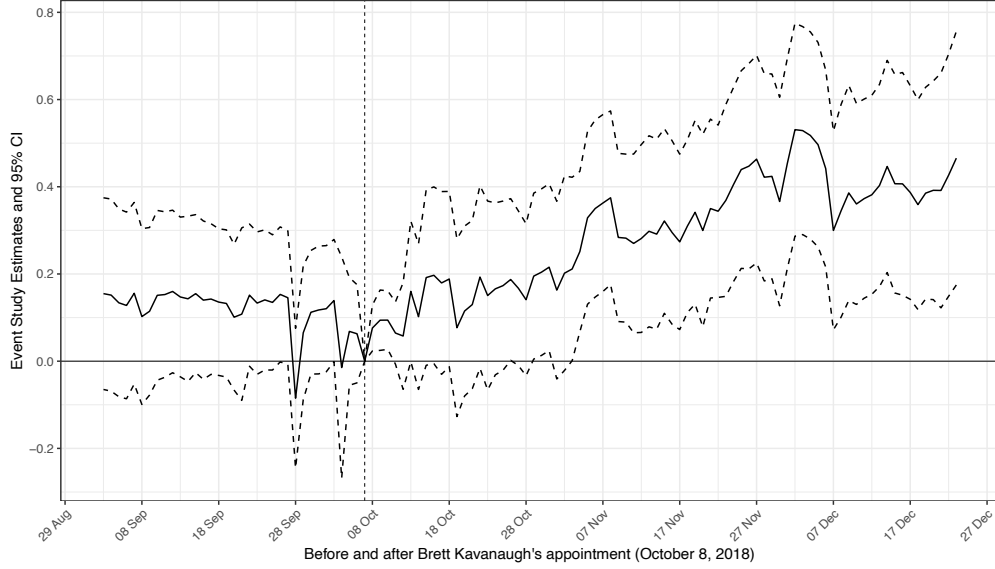


Figure 2.2. Event Study: $\log(\text{streams}_{it})$ - Songs by Female and Male Artists

Notes: In line with Equation 2.2, $\log(\text{streams}_{it})$ is regressed on song fixed effect and on the products between Female_i and a full set of dummy variables for each day from September 3, 2018, to December 23, 2018. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 8, 2018, is normalized to 0. The sample includes songs in the US top 200 Spotify Charts. Standard Errors (5%) are clustered at song level.

present the estimated β_τ from an event study analysis covering the period from September 2018 to August 2019 (250 days). This analysis confirms that the effect diminishes as public attention to the issue of sexual misconduct wanes.

4 Results

In this Section, we present the main results of our analysis. Table 2.2 shows four specifications of the DiD estimates of Equation 2.1. We focus on songs within the top 200 US charts on Spotify from September 3, 2018, to December 23, 2018. We employed four different specifications. Columns (1) and (2) use artist and day fixed effects, and controls including dummy variables about whether the song was released that week or whether it appeared in the chart the day before. In Column (2) we add song features controls, providing insights into the impact of time-invariant song characteristics. In Column (3), we incorporate song fixed effects. Finally, we focus on songs from single artists in Column (4) to avoid potential confounders related to collaborations of multiple artists. Standard

errors are clustered by artist in Columns (1) and (2) and by song in Columns (3) and (4).

In each specification, the coefficient β_1 in Equation 2.1 is positive and significant. This suggests that the increased media focus on discussions of sexual misconduct is having a positive impact on female artists, as evidenced by the increase in streams of their songs in the weeks following Brett Kavanaugh's appointment to the Supreme Court. The stronger effect observed with artist fixed effects can be partly attributed to the limitations of the specifications with song fixed effects. The panel of songs is highly unbalanced with many songs present in the charts for a few days or weeks. Thus, with song fixed effects, the coefficient β_1 is only estimated using songs present in the charts before and after October 8, 2018, which significantly limits the power of the empirical model and focuses on a specific set of songs. Similarly, excluding collaborations between artists of the same gender from the sample shrinks the sample by 30% and further reduces the group of (treated) songs by female artists, which is already a minority of the total songs.

Our analysis spans from early September 2018 to December 2018. This timeframe allows us to establish a sufficient number of days to detect parallel trends prior to October 8, 2018 (avoiding the inclusion of the summer period, which could be influenced by summer hits and potentially confound our analysis). It also provides enough days to observe the effect unfolding over the first 50 days and then being absorbed during the Christmas holiday period (see Figure 2.2). The period between Summer and Christmas in 2018 is expected to be relatively uneventful for the music industry, and we believe that seasonal dynamics should not significantly affect our estimates. To validate this assumption, we conducted a placebo analysis by repeating the event study specification as outlined in Equation 2.2 in 2017 and 2019 (Appendix Figures B.6 and B.7). In the corresponding period one year earlier or later, the difference in streaming for songs by female and male artists remains relatively constant over time.¹³ This leads us to conclude that seasonal events are unlikely to be highly influential and confound our estimates.

Similar to exogenous seasonal events, the effect of Kavanaugh's appointment could have been confounded by the release of singles or albums by a few top artists. The speci-

¹³In the fall of 2017, we observed the initial notable spikes in interest regarding the #MeToo movement, particularly in response to Alyssa Milano's tweet. However, there was no significant change in streams for either female or male artists during this period. This suggests that the scandals igniting the movement in 2017 were more closely associated with the film industry and did not directly affect music consumption.

Table 2.2. Difference-in-Differences: $\log(\text{streams}_{it})$ - Songs by Female and Male Artists

Dependent Variable:	Log(Streams)			
Model:	(1)	(2)	(3)	(4)
$\text{Post}_t \times \text{Female}_i$	0.295*** (0.088)	0.291*** (0.066)	0.176** (0.072)	0.157** (0.072)
<i>Fixed-effects</i>				
Artist	✓	✓		
Day	✓	✓	✓	✓
Song			✓	✓
Charts Controls		✓		✓
<i>Fit statistics</i>				
Standard-Errors	Artist		Song	
Observations	16,223	16,223	16,223	16,223
R ²	0.360	0.441	0.801	0.828
Within R ²	0.009	0.134	0.008	0.145

Notes: This table presents regression results analysing the impact of release timing and gender interactions on music streaming volumes. Columns (1) and (2) report results with standard errors clustered at the artist level, with Column (2) including release week dummies to account for initial release boosts and interactions between post-treatment periods and female artist identifiers, adjusted for artist fixed effects. Columns (3) and (4) use the same variables but adjust for song fixed effects, with standard errors clustered at the song level. Observations encompass 16,223 data points from the U.S. top 200 Spotify charts between September 3, 2018 and December 23, 2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

fications in Table 2.2 already include time-varying controls to account for songs that chart in the first week. However, to ensure that the effect is not primarily driven by a handful of top tracks, we rerun the four specifications presented in Table 2.2 without accounting for the top five songs in terms of daily streams. Appendix Table B.4 illustrates the results of this analysis, which shows a positive and statistically significant effect of similar size to the coefficients obtained with the full sample. Furthermore, to test the robustness of these findings, bootstrapping was performed on the sample by randomly removing 500 songs performed by female artists and re-running the event study for 1,000 iterations, shown in B.8. This additional bootstrapping analysis further supports the reliability of the results, providing confidence that the observed effects are not solely attributable to variations in individual high-performing tracks.

In all these specifications, the effect is not only statistically significant, but its size is also

economically relevant. Following Brett Kavanaugh’s appointment to the Supreme Court, songs by female artists saw a significant increase in streaming of at least 16%, which translates to over 50,000 additional Spotify streams per day. Given that the average length of songs by female artists is 3 minutes and 22 seconds, this translates to an additional 2,200 hours of songs by female artists per day.

We can also propose a back-of-the-envelope calculation of the financial impact of increased attention related to Kavanaugh’s appointment to the Supreme Court. Spotify does not explicitly disclose per-stream royalties, and the platform’s royalty structures appear to encompass more than just the number of song streams. However, various unofficial sources have suggested that Spotify pays artists an average of between 0.003 and 0.005 US dollars per stream.¹⁴

Based on this estimate, and assuming it is accurate, an increase of 43,000 Spotify streams per day would translate into a 129-219 US dollars increase in artists’ daily earnings for at least 8 weeks after Brett Kavanaugh’s appointment, for a total of more than 10,000 US dollar.

4.1. Spillover Effects

Using our identification design, we compare the evolution of streaming numbers between songs performed by female and male artists. The previous results indicate that the difference in streaming numbers between female and male artists favours female artists after October 8, 2018. However, based on the results in Table 2.2 and Figure 2.2, we cannot rule out that this change comes at the expense of reduced streams for songs by male artists. While this is not problematic for our design, it is critical to interpret correctly the results and understanding the impact of Kavanaugh’s appointment on music consumption.

The dataset only includes songs that appear in the top 200 US Spotify charts from September 3, 2018 to December 23, 2019. Thus, the increase in streams for a particular category of songs (such as those by female artists) can directly influence the composition of the top 200 songs on the platform over time. As shown in Appendix Figure B.11, the

¹⁴For more information about the Spotify royalty structure, see <https://support.spotify.com/us/artists/article/royalties/>, <https://loudandclear.byspotify.com/>, <https://dittomusic.com/en/blog/how-much-does-spotify-pay-per-stream/>, and <https://www.musicgateway.com/blog/music-distribution/how-much-does-spotify-pay-per-stream>.

share of songs by female artists in the US top 200 Spotify charts has increased, resulting in the displacement of songs by male artists and groups. However, the presence of this displacement effect within the top 200 charts does not necessarily imply that the coefficients presented in Table 2.2 capture the positive effects experienced by female artists together with the potentially negative consequences faced by male artists. This is due to our design, which involves comparing songs that are consistently present on the charts over time. While some songs by female artists may have replaced songs by male artists on the charts, this may not necessarily have affected artists who consistently maintain songs in the top 200.

To assess the potential spillover effect on songs within the charts, we analyse the streaming dynamics of songs by male artists before and after October 8, 2018. Appendix Figure B.12 illustrates the average values of $\log(\text{streams}_{it})$ for songs by male artists from September 3, 2018 to December 23, 2019. we do not observe a decrease in the number of streams following Kavanaugh’s appointment for songs by male artists. Instead, we observe a few isolated positive daily spikes before and after the October 8, 2018 “shock”. This finding suggests that the social movement-induced increase in streams for songs by female artists did not impact negatively songs by male artists in the US top 200 Spotify charts.

In Appendix Table B.3, we replicate the four specifications from Table 2.2, using songs performed by groups or collaborations of more than two artists as controls. Consistent with the main results, we also observe a positive effect in this case, indicating that streams of songs by female artists increased relative to those by groups after Kavanaugh’s appointment.

It is also important to recognize that songs by female artists are a minority. Thus, even if some listeners switched from songs by male artists or groups to those by female artists, the impact is unlikely to be significant given the significantly larger pool of songs by male artists. This is especially true given the differences in musical styles between male and female artists, as highlighted in Table 2.1. To account for these differences, we conduct a more focused analysis by narrowing our analysis to a subset of songs by male artists that share similar musical characteristics with those by female artists. To achieve this, we calculate a propensity score utilizing all Spotify song features and metadata. Then, for each day, we pair each song by a female artist with a song by a male artist using a nearest

neighbour approach.¹⁵ With this approach, we significantly reduce the group of songs by male artists used as a control group. Yet, when we estimate Equation 2.1 for this restricted sample, the results are similar to the ones using the whole sample of songs. As shown in Appendix Table B.2, the effect remains consistently positive and significant, with slightly larger estimates when artist fixed effects are included. Restricting to songs with similar characteristics does not pose a problem for pre-trends, as shown in Appendix Figure B.13. Here, the positive dynamics appear more pronounced, especially within the first 50 days, but we also see a decreasing trend that is consistent with the full sample analysis. Taken together, these results suggest that even when examining songs with similar characteristics - an aspect that might suggest an increased spillover potential - the magnitude of the effect remains comparable to the previous case.

4.2. A Platform-Induced Effect?

Up to this point, we have interpreted the increase in music streams as a sign of changing preferences among Spotify users for songs by female artists. However, Spotify’s recommendation system also influences the music users come across on the platform, and the surge in streams may be partly due to platform recommendations. Unfortunately, we do not have enough data to directly evaluate if Spotify’s recommendation algorithm changed during the Fall of 2018.

However, we do have some knowledge about the songs the platform promotes to its listeners through the “New Music Friday” playlist. This playlist is considered a key platform for promoting newly released tracks across various genres. It is highly visible and often listened to by Spotify users eager to discover new music tracks. The playlist is updated every week and includes a variety of well-known and unknown songs. Previous studies have demonstrated the significance of the “New Music Friday” playlist and how it can be used by Spotify to effectively promote independent or female artists (Hukal, Henfridsson, Shaikh and Parker, 2020; Aguiar and Waldfogel, 2021; Aguiar et al., 2021).

Appendix Figure B.14 shows the percentage of male and female artists and groups featured in the “New Music Friday” playlist over time. During the Fall of 2018, there was

¹⁵As distance metric to calculate the nearest neighbour we use the scaled Euclidean distance. This is to mimic the Euclidean distance of normalized vectors used and implemented by Spotify in the Approximate Nearest Neighbour package: <https://github.com/spotify/annoy>.

no significant increase in female artists showcased. If anything, male artist representation increased in November and December 2018. This observation alone cannot rule out the platform’s impact on more song streams by female artists. However, it suggests that Spotify did not actively promote female artists through one of their main playlists during our study period.

4.3. Songs Lyrics and Sexism

The analysis has focused primarily on the impact of Kavanaugh’s appointment on the streams of songs by female artists. However, the increasing attention in gender-related policies and sexism may have some impact on the language used in songs, regardless of the gender of the artist. This raises the question of whether the lyrical content of songs plays a role in determining their success. While it is unlikely that a sudden surge of non-sexist songs will be produced in the immediate aftermath of Kavanaugh’s appointment, we can examine whether lyrics might influence listener preferences.

In Appendix Figure B.15, we show the daily proportion of songs with at least one sexist line in the lyrics by female and male artists and groups from September 2018 to January 2019. Songs by female artists are significantly less likely to contain sexist language than those by male artists or groups. Yet, we do not observe a large change in the proportion of songs with sexist lyrics before and after October 2018. There is a sharp decrease in sexism around the Christmas holiday season, likely due to the release of more festive tunes that tend to be less controversial. If, instead of focusing on the presence of at least one sexist lyric, we examine the proportion of sexist lyrics, we still observe that songs by female artists are less sexist and the presence of sexism in songs does not change much over time (Appendix Figure B.16).¹⁶

Despite the lack of a pronounced change in overall lyrical sexism, the effect we observed for women’s songs could still be partially attributed to the language of their songs. To investigate this possibility, we repeated our analysis, dividing the sample into songs with and without sexist lyrics. We found that songs with sexist content (with at least one sexist

¹⁶The lack of a clear post-Kavanaugh pattern in lyrical content may reflect the limitations of our analysis timeframe. While user preferences may have shifted toward less sexist material, the pool of songs available during the weeks of interest may not have changed significantly. This shift is more likely to manifest itself over a longer period.

word in the song’s lyrics) accounted for 49% of the total, with 320 songs containing sexism by male artists and 10 by female artists.

In our analysis of songs by male and female artists that contain at least one sexist line, we observe a stronger positive effect. Specifically, songs by female artists experience a 50% increase in daily streams following Kavanaugh’s appointment, regardless of the specification used (see Table B.5). This more pronounced effect is consistent with the temporal patterns identified in the previous event studies. Figure B.17 illustrates this trend, repeating the specification from Equation 2.2 but focusing only on songs with at least one sexist line in their lyrics. We observe a significant increase in streams for female artists immediately after October 9, 2018. In this scenario, the uptick is not only more robust in the first few weeks, but also continues to grow over time. Conversely, when looking at songs without sexist lyrics, the effect remains positive but only reaches statistical significance when artist fixed effects are applied. This effect is much less pronounced and mostly localized to the first weeks after Kavanaugh’s appointment (as shown in the Appendix Table B.6 and Figure B.18).

These results support the hypothesis that the presence of sexism in lyrics is a relevant channel of the observed effect. Specifically, songs by female artists receive more streams than those by male artists in the context of lyrics containing sexist terms. This differential effect may arise because when female artists incorporate sexist terms, the valence and interpretation of these words may be perceived differently, potentially less offensively, than when used by male artists (Galinsky, Wang, Whitson, Anicich, Hugenberg and Bodenhausen, 2013; Cervone, Augoustinos and Maass, 2021).

4.4. Song Lyrics and Female Empowerment

In this analysis, we employ a difference-in-differences (DiD) approach to evaluate the impact of songs classified as “empowering” on music streaming volumes, distinguishing between songs by female and male artists. Using the LLAMA 3 model,¹⁷ songs are classified as empowering based on varying threshold levels and prompt configurations to assess robustness and sensitivity of the results.

¹⁷LLAMA 3 is a state-of-the-art language model developed by Meta AI, designed to understand and generate human-like text based on the input it receives. It is particularly effective in natural language processing tasks, including text classification and sentiment analysis.

As shown in Table B.7, we begin by examining the effect of empowerment on streaming with samples restricted to male and female artists at a threshold of 0.75. This table also distinguishes results by prompt type, allowing us to isolate the gender-specific influence of empowering content while accounting for potential sampling biases. The results reveal that empowering songs by female artists have a distinct impact on streaming, with positive and statistically significant interaction terms. For instance, the interaction coefficient between $\text{Post}_i \times \text{Female}_i \times \text{Empowering}_i$ is 0.315, significant at 5%, indicating that empowering songs by female artists are associated with a 31.5% increase in streaming compared to the baseline.

Next, Table B.8 explores the effect of empowerment classification with progressively stricter thresholds set at 0.65, 0.7, and 0.75. This variation in thresholds helps examine how increasingly stringent definitions of “empowerment” influence streaming outcomes. The coefficients in this table show a significant interaction between the post-event period, female artist, and empowerment status, with the highest threshold of 0.75 yielding a significant coefficient of 0.288 at 5%. This result suggests that the impact of empowering content for female artists becomes more pronounced as the empowerment threshold increases, reinforcing the interpretation that higher streaming levels are tied to stricter empowerment criteria.

Finally, in Table B.9, we analyze the effect of different prompt engineering configurations (blind, sighted, and examples) on the classification of songs as empowering by the LLAMA 3 model, while maintaining a constant threshold of 0.75. Prompt engineering plays a critical role in refining the model’s classification process. In the “blind” configuration, the model is not provided with any information about the gender of the performer, ensuring a neutral assessment that does not rely on gender-specific cues. The “sighted” configuration introduces the performer’s gender as additional information, enabling the model to contextualize its classification based on gender. Lastly, the “examples” configuration includes illustrative samples of empowering language for both male and female artists, helping the model identify empowerment characteristics in a more gender-tailored manner. This design allows us to evaluate how these different prompt setups influence the model’s classification accuracy and the corresponding regression coefficients. The results reveal that prompt engineering significantly impacts the magnitude and significance of the

interaction terms.

Overall, these findings suggest that empowering songs by female artists experience higher streaming levels post-event, particularly when classified with a high threshold and appropriate prompt engineering. This pattern, consistently observed across multiple model specifications, underscores the robustness of the positive interaction effect of empowering content by female artists on streaming volumes.

4.5. Robustness checks

The analysis presented in Figures B.9 and B.10 explores the robustness of the estimated treatment effects from the Difference-in-Differences regression described in Equation 2.1 by examining variations across both geographical and temporal dimensions.

Figure B.9 illustrates the results of the event study for songs by female and male artists, stratified by country. The coefficients, along with their 95% confidence intervals, are estimated for Canada (CA), Great Britain (GB), the United States (US), France (FR), and Italy (IT). This country-level disaggregation highlights the consistency of the treatment effects across distinct geographical contexts. The inclusion of standard errors clustered at the song level ensures robust inference, mitigating potential biases arising from within-song correlation.

Figure B.10, on the other hand, focuses on the temporal dimension by stratifying the analysis by year within the US. The yearly estimates provide insights into the stability of the treatment effects over time. As with the country-level analysis, standard errors are clustered at the song level to maintain the reliability of the inference. This temporal disaggregation allows us to observe whether the effect of the treatment is persistent or varies across different years. Together, these analyses provide compelling evidence of the robustness of the treatment effects, both across countries and over time, reinforcing the validity of the findings.

5 Conclusion

Based on our analysis of Spotify streaming data, we find that the appointment of Brett Kavanaugh to the Supreme Court led to a notable increase in the consumption of music

performed by female artists. Specifically, our analysis indicates a 16% rise in streaming numbers for songs by female artists on Spotify, a shift that persisted for several weeks. This change, robust against various confounding factors, highlights a significant alteration in consumer behaviour in response to a major socio-political event.

Notably, this increase in streaming is not merely reflective of changing music preferences, but also signals consumer alignment with broader social movements focused on gender issues. Our findings align with and extend the work of [Luo and Zhang \(2022\)](#), who noted changes in the hiring of female film writers following the Weinstein scandal, and [Levy and Mattsson \(2023\)](#), who documented a surge in reporting sexual crimes in countries with prominent #MeToo movements. This parallel suggests a broader societal shift towards acknowledging and addressing gender-related concerns.

This behavioural shift towards content created by female artists underscores a significant opportunity for businesses. By aligning their offerings with evolving consumer values, particularly in contexts where gender and social issues are prominent, businesses can not only stay relevant but also contribute positively to societal change. For platform designers and managers, it is crucial to understand and anticipate how external events might shape consumer preferences. This foresight is essential for ensuring that their platforms can swiftly adapt to these changes, thereby fostering an environment that is both responsive and responsible.

Ultimately, our study adds a new dimension to the discourse on political consumerism and the design of digital marketplaces. It highlights the dynamic nature of consumer preferences influenced by external events and underscores the importance of businesses and platforms in being attentive to these shifts, especially in the context of gender and social issues.

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Chapter 3

Picture Perfect? The Impact of Images on Sales in Second-Hand Marketplaces



1 Introduction

Second-hand online marketplaces have experienced remarkable growth over the past decade, offering users the ability to buy and sell a diverse range of items, including books, furniture, electronics, and, most prominently, clothing. Platforms like Vinted have exemplified this trend, with revenue increasing from \$10 million in 2017 to nearly \$600 million in 2023, reflecting growing consumer demand for affordable, sustainable, and convenient shopping alternatives¹. Within these marketplaces, the fashion industry and e-commerce converge on a shared dependency on visual appeal to drive consumer decisions. While the fashion industry often employs professional models to present items in the most attractive light, e-commerce relies on images to bridge the gap between digital and physical shopping experiences. On peer-to-peer platforms, sellers are responsible for designing ads, facing the choice to select the main image to attract buyers' attention. This raises a critical question for sellers: should they use real-life images that might compromise their privacy or rely on alternative formats, such as stock images? Choosing an image involves varying levels of effort, cost, and privacy considerations. Sellers must balance these factors to optimize sales outcomes, navigating a marketplace where visual presentation can significantly influence the success of a listing.

This study leverages data from Tise.com, Norway's largest second-hand marketplace, with over 1 million listings from January to December 2023. By employing computer vision techniques, I classify listing photos into categories: clothing alone, real person, catalogue image, or professional model. Picture quality is assessed using no-reference metrics, providing a detailed view of visual presentation strategies. Linking these attributes to sales data, the analysis reveals that professional images are predominantly used for higher-priced items, while lower-priced listings favour clothing-alone photos. Interestingly, real-person images have minimal impact on sales, indicating sellers' strategic use of professional visuals for premium listings. The analysis highlights significant differences in how visual presentation impacts sales performance across product categories. Catalogue images prove especially effective, greatly increasing the chances of sales for items

¹<https://www.statista.com/statistics/1405644/vinted-revenue/>

like pants and jackets. Buyers in these categories tend to prioritize clear and consistent product visuals. High-quality, professional images help signal product reliability in marketplaces where information is limited, building trust and making it easier for buyers to make confident decisions.

The study further investigates the determinants of image selection by applying regression analysis to uncover the factors influencing sellers' choices regarding visual effort and presentation style. This approach uncovers how sellers tailor their image strategies in response to both product characteristics and buyer preferences.

1.1. Related literature

This study draws on and contributes to two key streams of literature: (1) consumer behaviour in second-hand and peer-to-peer marketplaces, (2) the role of visual presentation in online decision-making. By integrating insights from these domains, it addresses critical gaps in our understanding of how image presentation, seller reputation, and product attributes interact to influence consumer decision-making in second-hand fashion platforms.

Second-hand markets have gained significant scholarly attention due to their alignment with consumer motivations such as perceived value, environmental consciousness, and economic benefits. Platforms like Vinted, Poshmark, Depop, and Vestiaire Collective have evolved to meet these diverse needs through features like social networking, product authenticity checks, and niche targeting for luxury or trend-conscious buyers. Prior research highlights how mechanisms like reputation systems, reviews, and detailed product descriptions reduce information asymmetry and foster trust between buyers and sellers (Filippas, Horton and Golden, 2022; Luo, Kannan and Ratchford, 2008). However, the specific role of platform design in shaping consumer behaviour within second-hand markets, which rely heavily on trust and authenticity, remains underexplored.

A growing body of literature emphasizes the importance of visual presentation in shaping online consumer perceptions. Studies show that visual cues, such as high-quality images and appealing product displays, often outweigh other factors like product descriptions and seller ratings in influencing buyer behaviour (Belém, Maros, Canuto, Silva, Almeida and Gonçalves, 2019). Platforms encourage sellers to optimize visual presentation through strategies like natural lighting, detailed photography, and modelled images,

aligning with broader trends in personal branding and visual storytelling (Ma, Mezghani, Wilber, Hong, Piramuthu, Naaman and Belongie, 2019). Research on the impact of profile pictures has highlighted the importance of aligning visual appearance with expected characteristics in achieving favourable outcomes. Troncoso and Luo (2023) investigated the concept of “looking the part”, demonstrating that individuals whose appearance aligns with professional or societal expectations are more likely to experience positive results in hiring scenarios. Their findings suggest that visual cues play a significant role in shaping perceptions of competence, trustworthiness, and suitability, which can directly influence decision-making processes. Yet, while the role of imagery in professional and generalized e-commerce has been extensively studied, the unique dynamics of visual presentation in second-hand markets, where issues like product wear-and-tear and authenticity are critical, have not been thoroughly investigated.

This study provides a holistic analysis of the factors influencing sales performance in second-hand marketplaces, focusing on the interplay between image presentation, seller reputation, buyer trustworthiness, and the overall effort seller invested in curating their listings image choice, controlling for other idiosyncratic listings’ characteristics, such as caption. Beyond product-level variables, the analysis incorporates critical seller characteristics such as the presence of profile pictures and beauty of user, accumulated reviews. These dimensions capture not only the functional aspects of product presentation but also the personal and stylistic elements that shape buyer perceptions of trustworthiness and engagement. By integrating these perspectives, the research extends existing literature on visual presentation, reputation mechanisms, and buyer trust in online marketplaces. It offers actionable insights for sellers to optimize their visual strategies across product categories while addressing the nuanced interactions between presentation style, seller attributes, and buyer expectations. These findings contribute to a deeper understanding of how personal and stylistic dimensions of image presentation influence sales outcomes in digital peer-to-peer environments.

2 Data

This study utilizes data from Tise, a prominent second-hand fashion platform primarily serving the Nordic region, including Norway, Sweden, Denmark, and Finland. Tise facilitates the buying and selling of pre-owned fashion items by integrating various features designed to enhance user experience and ensure transaction safety. Key functionalities of the platform include an integrated payment solution that secures transactions, a robust search system allowing users to filter by specific categories and brands, and opportunities for users to generate additional income through reselling. A strong emphasis on sustainable shopping is central to Tise’s mission, promoting the reuse and recycling of fashion items to support environmental conservation efforts. Users can upload photos of their items to list them for sale, while also accessing features that highlight the latest fashion trends. This dual focus not only aids users in staying updated with current styles but also encourages responsible consumer behaviour through second-hand shopping.

The community aspect of Tise is significant, with millions of active users interacting within the platform to create a dynamic marketplace environment. This extensive user base drives economic activity and fosters a sense of community among second-hand fashion enthusiasts. The platform’s design elements, such as reputational systems and product presentation features, play crucial roles in influencing purchasing decisions and building trust among users. For the purposes of this analysis, the dataset is restricted to adult clothing apparel, excluding categories such as child and baby items, interior and furniture, outdoor gear, art and design, devices and audio, and leisure and hobbies. These excluded categories are retained solely for constructing metrics related to reputation and user experience within the marketplace.

2.1. Data Collection

The dataset for this study was collected from Tise.com using a hidden API, yielding over 10 million data points across four countries, collected between January 2016 and March 2024. To enhance analytical focus and control, the dataset was refined to include only female users from Norway. This approach addresses potential confounding factors such as differences in legislation, cultural practices, currency systems, and consumer be-

haviours across the Nordic countries. Norway’s position as the origin country of Tise, coupled with its highest platform usage rate, provides a uniquely rich and concentrated dataset. Furthermore, the Norwegian market is characterized by minimal competition in the second-hand marketplace sector, creating an environment free from significant external market influences that could obscure the platform-specific dynamics under study.

Focusing on Norway offers unique advantages, despite the narrower scope. The country’s mature and dominant engagement with Tise ensures a complete dataset, capturing user histories in their entirety, a rarity in more fragmented or competitive markets. This granularity enables a robust analysis of long-term trends and behaviours, which might otherwise be obscured in datasets with missing or inconsistent user records.

While the cultural and regulatory specificity of Norway may limit the direct applicability of findings to other contexts, this controlled environment minimizes the noise introduced by cross-country differences, such as variations in currency systems or market competition. By isolating the dynamics of a single, cohesive market, this study ensures a high level of analytical precision. Moreover, the absence of significant competitors in Norway allows the analysis to focus on the interactions between platform features, user behaviours, and market outcomes, without external distortions.

This trade-off between generalizability and analytical depth underscores the value of the Norwegian dataset. The findings, though context-specific, offer transferable insights into user behaviour, platform design, and the role of visual presentation in peer-to-peer marketplaces. By prioritizing data completeness and reducing external variability, the study provides a rigorous foundation for understanding broader dynamics in the second-hand marketplace sector, informing both theoretical advancements and practical strategies in platform development.

After creating a subset, the dataset comprises 4,948,284 observations across 22 categories. Each observation corresponds to an individual product listing. The data collected for each product includes variables such as category, condition, country of origin, reference gender, price, creation date, size, update date, brand, sold status, caption, colours, and likes count. At the user level, the dataset encompasses the entire wardrobe of each user, including the history of sold products, review counts, review texts, and average ratings.

2.2. Data Description

The data analysed in this study reveals significant gender-based patterns in user demographics and product offerings within the marketplace. The majority of users are female (67.29%), while males constitute 10.09%. Additionally, 21.72% of users prefer not to disclose their gender, and a small minority (1.40%) identify as "Other." Correspondingly, product offerings are predominantly targeted toward females (65.52%). Products labelled as gender-neutral account for 12.61%, while those intended for males represent 4.54%. These trends highlight the marketplace's strong orientation toward female users and products, suggesting potential implications for gender-specific marketing strategies.

Weekly product postings, categorized by target gender, reveal a pronounced and increasing prevalence of female-oriented products from 2020 onward. In contrast, postings for male-oriented, gender-neutral, and unspecified categories have remained relatively stable and significantly lower. This trend underscores a gender skew in the marketplace, suggesting a greater focus on female-oriented products, potentially driven by demand or supply dynamics.

The platform has undergone significant changes over time, particularly in areas such as condition disclosure, brand identification, user reviews, and product condition distribution. These trends suggest that the platform has evolved into a more structured and transparent marketplace.

Descriptive statistics provide an overview of item features such as price, condition, size, and textual attributes. For instance, the majority of items are priced in the lower range, are in "New" or "Lightly Used" condition, and are of size "S". Additionally, caption lengths vary widely, with a significant number of items lacking captions altogether.

Overall, these findings offer a comprehensive view of the platform's user base, product listings, and evolutionary trends. Further details and visual representations can be found in the appendix.

2.3. Developing variables related to images

Labelling the pictures as Homemade Cloth, Real Person, Catalogue Image, Professional Model

The image analysis was conducted using a model trained with YOLOv8 by Ultralytics². Initially, the YOLOv8 large classification weights, pre-trained on a broad dataset, were fine-tuned to develop a custom model. The model achieved an 89% success rate in out-of-sample validation.

Given the impracticality of manually analysing all images, a semi-supervised learning approach was employed. First, a training set was created for the “tops” category, starting with 500 training images, and 100 validation images. This process was iterated six times, ultimately expanding the dataset to 1,600 training images and 500 validation images. The lower bound for validation images resulted from the under-representation of the “Professional Clothing” category.

In this approach, the initially trained model was used to label additional images. These automatically labelled images were then manually reviewed, and the corrected labels were used to retrain and improve the model further.

The refined model was subsequently applied to categorize images for “Jumpsuits” “Skirts” and “Pants” These categories were selected to represent the “top” “full-body” and “bottom” segments of clothing, respectively.

The last step involved training the classifier using the pre-trained YOLOv8 large model, fine-tuned over 100 epochs. I utilized 62,5% of the 3.200 labeled images for training and 37,5% for validation. The YOLOv8 model, already equipped with robust transfer learning Hartmann et al. (2021), Zhang et al. (2021), and Zhang and Luo (2022), data augmentation (Krizhevsky, Sutskever and Hinton, 2012), and regularization techniques (Srivastava et al., 2014), effectively mitigates overfitting without requiring additional manual intervention. This streamlined approach allowed us to achieve high performance with minimal adjustments to the standard training process. Once classified, a dummy variable was generated according to the type of subject in the picture.

²<https://www.ultralytics.com>

To create the control variables, I utilized a combination of open-source models. The presence of a person in the image was detected using the MiVOLO model ([Kuprashevich and Tolstykh, 2023](#)), which also provided estimates for the person's age. For assessing beauty, I employed the CLIP model, applying it to image crops generated by MiVOLO.

Image Quality Analysis

For the image quality analysis (IQA), I employed a range of seven objective quality metrics and one combined aesthetics and quality score. The metrics included BRISQUE, NIQE, MUSIQ, DBCNN, PAQ, PIQE, and IL-NIQE, each evaluating distinct aspects of image fidelity and aesthetic appeal. Together, these metrics provide a comprehensive framework for assessing the quality of product images in the dataset³.

In addition to these metrics, a subset of 15,000 images was analysed using the Q-Align Score ([Wu, Zhang, Zhang, Chen, Li, Liao, Wang, Zhang, Sun, Yan, Min, Zhai and Lin, 2023](#)), which integrates aesthetics and quality evaluations into two comprehensive measures. Q-Align is particularly valuable for analysing the alignment between image quality and aesthetic appeal, offering a holistic perspective on how visual presentation impacts consumer perceptions. The Q-Align scores from this subset were then used to train a machine learning model, specifically a random forest, to predict Q-Align scores across the entire sample.

Profile Picture Analysis

In this study, profile pictures were analysed to extract and quantify a range of visual characteristics, with a primary focus on using the image as a proxy to infer the perceived beauty of the seller. The Beauty score, detailed further in the appendix, was calculated using a CLIP model⁴, which evaluates the aesthetic appeal of the person in the profile picture. This score serves as a measure of the visual impression conveyed by the seller's profile image, providing a proxy for perceived attractiveness in buyer-seller interactions.

In addition to the beauty score, detailed facial and body key points were extracted,

³Further information on the scores can be found in the Appendix C

⁴CLIP (Contrastive Language-Image Pretraining), a neural network model developed by OpenAI, aligns visual and textual representations by training on a large dataset of images and corresponding text.

including the positions of the nose, eyes, ears, shoulders, elbows, wrists, hips, knees, and ankles. These data enable a fine-grained analysis of the posture and orientation of the subject in the profile picture, offering additional insights into how stylistic and personal presentation might influence buyer perceptions.

Variables such as age and gender were estimated using the MiVOLO ([Kuprashevich and Tolstykh, 2023](#)) model, recognized for its high accuracy in demographic classification. Other metrics included the number of faces (`n_faces`) and the number of persons (`n_persons`) present in the profile picture, adding context to the type and focus of the images used by sellers.

3 Empirical Framework

This analysis focuses on understanding the dynamics of marketplace outcomes by examining the influence of various factors, with particular attention to the *image category* in the first product image. The person category captures the presentation style of the item, which can take four distinct values: *Informally presented cloth*, *Catalogue image*, *Professional model*, and *Real person*.

I hypothesize that the presentation style significantly influences both the likelihood of a sale and the time it takes for a product to sell. Our analysis proceeds by investigating three primary aspects of marketplace dynamics. First, I examine the factors influencing the choice of the listing's picture. This analysis employs a logistic regression model to explore how product characteristics, seller reputation, and, critically, the person category of the first image impact sellers' price-setting behaviour. Second, I assess the likelihood of a product being sold by modelling the binary outcome (whether the product sells) as a function of pricing, seller reputation, and product presentation, with particular attention to the *image category* of the first picture, which is expected to play a crucial role in capturing consumer attention and driving sales.

The following sections will detail the econometric models employed for each dimension of the analysis and provide a comprehensive interpretation of the results.

3.1. Image choice model

$$\begin{aligned} \text{Image Choice}_{i,j,t} = & \alpha_i + \beta_0 \cdot \text{Product Characteristics}_i + \beta_1 \cdot \text{Ad Characteristics}_i \\ & + \beta_2 \cdot \text{Price}_i + \beta_3 \cdot \text{User Reputation and Experience}_j \\ & + \beta_4 \cdot \text{Brand Reputation}_{j,t} + \beta_5 \cdot \chi_{i,j} + \varepsilon_{i,j,t} \end{aligned} \quad (3.1)$$

The model structure accounts for various predictors influencing image choice, including product characteristics, listing features, price tier, user reputation and experience, and brand reputation. These predictors capture the key dimensions that may shape sellers' decisions regarding the type of image to use, whether professional, self-taken, or featuring a person. The other controls further refine the analysis.

By incorporating Fixed Effects, the logistic regression model effectively controls for unobserved characteristics specific to categories, such as jackets, dresses, or pants, which might influence image selection. This ensures that the analysis isolates the effects of the included predictors on image choice, without being confounded by unmeasured category-level variation.

The logistic regression approach provides interpretable estimates of the factors associated with different image categories. This aligns with the study's objective of understanding how sellers decide on the presentation of their products in second-hand marketplaces.

3.2. Sale outcome model

To examine how image category influences the likelihood of a product being sold, I employ a logistic regression model. Logistic regression is well-suited for binary outcomes, such as the choice of image category or sale occurrence, providing robust estimates of the relationship between predictors and the dependent variable. Additionally, it allows for the inclusion of Fixed Effects (FE), enabling control for unobserved heterogeneity across categories.

Using a logistic regression model, the analysis provides interpretable estimates of how predictors relate to the probability of a sale. The focus on image category allows for an

exploration of how different types of visuals, such as professional or self-taken images, contribute to the perceived value and attractiveness of a listing. The use of Fixed Effects ensures that these estimates are not biased by unobserved differences across categories.

This approach aligns with the study's objective of understanding the determinants of successful sales and provides robust insights into the role of image category in influencing buyer behaviour.

$$\begin{aligned}
\text{Sale Outcome}_{i,j,t} = & \alpha_i + \beta_0 \cdot \text{Picture Category}_i + \beta_1 \cdot \text{Product Characteristics}_i \\
& + \beta_2 \cdot \text{Ad Characteristics}_i + \beta_3 \cdot \text{Price}_i \\
& + \beta_4 \cdot \text{User Reputation and Experience}_j \\
& + \beta_5 \cdot \text{Brand Reputation}_{j,t} + \beta_6 \cdot \chi_{i,j} + \varepsilon_{i,j,t}
\end{aligned} \tag{3.2}$$

Further variable description can be found in the appendix C

4 Results

This section presents the findings, summarized in the tables and figures below.

4.1. Drivers of Image Choice

This subsection examines the factors influencing users' selection of image types when creating ads on the platform. The choice of image, ranging from homemade photos of the fabric and images featuring a real person to catalogue images and professional model photos—is shaped by variables such as price quintile, product characteristics, brand perception, and seller activity metrics. The results, presented in Table 3.1 for the full sample, indicate a strong association between higher price quintiles and the use of professional-grade visuals (catalogue images and model photos). This suggests that sellers are more likely to invest in high-quality images for higher-value items, aligning their strategies with buyer expectations.

Notably, price exhibits a strong negative association with the use of homemade images, whereas images featuring a real person show a modest positive correlation. Category-

Table 3.1. Logistic Regression on Picture Type choice for All Products

Dependent Variables: Category Model:	Homemade Image	Real Person	Catalogue Image	Professional Model
	Full sample			
	(1)	(2)	(3)	(4)
Price Quintile: Linear	-0.971*** (0.170)	0.191* (0.103)	0.738*** (0.127)	0.949*** (0.106)
Condition Disclosed	0.147*** (0.039)	-0.034 (0.042)	-0.030 (0.083)	-0.154** (0.073)
Log(1 + Reviews at Posting)	-0.200*** (0.011)	0.097*** (0.014)	0.104*** (0.017)	0.148*** (0.008)
Log(1 + (Posted - Sold))	0.041 (0.030)	0.067*** (0.018)	-0.072*** (0.010)	-0.113*** (0.015)
Log(Posted)	0.062* (0.034)	-0.057** (0.028)	-0.077** (0.025)	0.003 (0.010)
Beauty	-0.021*** (0.001)	0.016*** (0.0004)	0.002*** (0.0006)	0.011*** (0.001)
Number of Images	-0.007 (0.028)	0.066** (0.029)	-0.237*** (0.020)	0.038 (0.037)
Brand	✓	✓	✓	✓
Caption	✓	✓	✓	✓
Color	✓	✓	✓	✓
Material	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓
Size	✓	✓	✓	✓
Year	2023	2023	2023	2023
<i>Fixed-effects</i>				
Category	✓	✓	✓	✓
<i>Fit statistics</i>				
Standard-Errors			Category	
Observations	888,628	888,628	888,628	888,628
Squared Correlation	0.142	0.055	0.034	0.081
Pseudo R ²	0.108	0.049	0.053	0.086
BIC	1,099,863.2	954,556.3	434,185.6	779,919.2

Notes: This table presents logistic regression results analysing the determinants of image type choice in product listings on a second-hand marketplace. The dependent variables represent different image categories: Homemade Image, Real Person, Catalogue Image, and Professional Model. The regression includes the full sample with 5 product categories and a total of 888,628 observations. Controls for brand, caption length, colour, material, month of posting, and size are included. Fixed effects are applied at the category level. Standard errors are clustered by category. * p < 0.10, ** p < 0.05, *** p < 0.01.

specific results for sweaters, tops, pants, dresses, and jackets are detailed in Appendix Tables C.4 to C.8.

Across all categories analysed, there is a strong and consistent association between higher price quintiles and the choice of professional-grade images, specifically cloth professional and person professional. This pattern indicates that sellers strategically invest in polished visuals for higher-value items, aligning their presentation with buyers' expectations for premium products. In contrast, lower price quintiles are more frequently associ-

ated with more accessible image choices, such as using a self-portrait or taking a photo of the garment at home, reflecting a reduced level of seller effort for lower-value items.

The beauty category is another important determinant influencing picture choice. Across all categories, items with higher beauty scores are more likely to feature their own image. This suggests that sellers recognize the value of leveraging aesthetic appeal through their image presentation. Although the magnitude of the beauty category's effect is smaller than that of price quintiles, it remains statistically significant and consistent across product types, reinforcing the importance of visual aesthetics in influencing picture choice. It is noteworthy that when sellers choose not to disclose the condition of the garment, they are more likely to use professional catalogue images. This behaviour suggests a potential attempt to avoid featuring the actual item in the first picture, possibly to obscure the garment's true condition.

4.2. Sale outcome

The analysis reveals substantial heterogeneity in the impact of visual presentation on sales performance across product categories. Catalogue images significantly enhance the likelihood of sales for most categories, particularly for items such as pants and jackets. In these categories, buyers prioritize clarity and uniformity in product presentation, which aligns with the predictions of signalling theory. Polished, professional images serve as credible signals of product quality in marketplaces characterized by high information asymmetry, thereby fostering trust and facilitating buyer decisions.

In contrast, real-person images are more effective in categories like dresses, where the ability to demonstrate fit and style is particularly valued. This finding suggests that buyers in these segments respond positively to personalized cues that help them envision how the product might look or function in their own context, reflecting principles of consumer engagement and emotional purchasing. However, the analysis also uncovers instances where real-person images negatively affect sales outcomes. For categories such as sweaters and pants, overly personalized imagery may detract from buyers' focus on the product itself, potentially undermining its perceived quality or relevance.

These findings contribute to a nuanced understanding of how visual presentation interacts with product characteristics to shape consumer behaviour in second-hand fashion

Table 3.2. LogisticRegression Sold (0/1)

Dependent Variable: Category Model:	Full sample (1)	Sweaters (2)	Tops (3)	Pants (4)	Dresses (5)	Jackets (6)
Price Quintile: Linear	0.426*** (0.039)	0.501*** (0.012)	0.497*** (0.016)	0.345*** (0.012)	0.344*** (0.010)	0.417*** (0.014)
Price Quintile: Quadratic	0.051** (0.022)	0.049*** (0.011)	0.198*** (0.015)	0.008 (0.011)	0.040*** (0.009)	0.012 (0.012)
Price Quintile: Cubic	-0.022* (0.013)	-0.019* (0.011)	0.037** (0.015)	-0.069*** (0.010)	-0.015* (0.008)	-0.015 (0.011)
Condition Disclosed	-0.160** (0.080)	-0.081 (0.097)	0.168 (0.160)	-0.290** (0.119)	-0.091 (0.103)	-0.437*** (0.129)
Real Person	0.030 (0.090)	-0.119*** (0.014)	-0.010 (0.018)	-0.126*** (0.015)	0.289*** (0.011)	0.037** (0.015)
Catalogue Image	0.217** (0.096)	0.106*** (0.021)	0.369*** (0.029)	-0.099*** (0.024)	0.436*** (0.020)	0.166*** (0.021)
Professional Model	0.232 (0.145)	0.056*** (0.018)	0.117*** (0.021)	-0.036** (0.016)	0.609*** (0.013)	0.136*** (0.020)
Beauty	-0.001*** (0.0003)	-0.0009** (0.0004)	-0.0008* (0.0005)	-0.0008** (0.0004)	-0.0010*** (0.0003)	-0.002*** (0.0004)
Person in Profile Picture	0.119*** (0.009)	0.122*** (0.023)	0.101*** (0.030)	0.119*** (0.022)	0.118*** (0.018)	0.154*** (0.024)
Log(Brand Products)	0.026* (0.015)	0.018*** (0.003)	-0.017*** (0.004)	-0.005* (0.003)	0.052*** (0.002)	0.065*** (0.003)
Brand Perception	0.112*** (0.024)	0.110*** (0.005)	-0.0003 (0.006)	0.107*** (0.005)	0.148*** (0.004)	0.183*** (0.006)
Log(1 + Reviews at Purchase)	0.396*** (0.021)	0.453*** (0.004)	0.425*** (0.006)	0.416*** (0.004)	0.354*** (0.003)	0.364*** (0.005)
Log(1 + (Posted - Sold))	-0.581*** (0.016)	-0.627*** (0.004)	-0.580*** (0.005)	-0.600*** (0.004)	-0.552*** (0.003)	-0.553*** (0.004)
Log(1 + Number of Likes)	0.148*** (0.022)	0.139*** (0.005)	0.183*** (0.007)	0.149*** (0.005)	0.071*** (0.004)	0.178*** (0.006)
Caption	✓	✓	✓	✓	✓	✓
Color	✓	✓	✓	✓	✓	✓
Image Quality	✓	✓	✓	✓	✓	✓
Material	✓	✓	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓	✓	✓
Size	✓	✓	✓	✓	✓	✓
Years	2023	2023	2023	2023	2023	2023
<i>Fixed-effects</i>						
Category	✓	✓	✓	✓	✓	✓
<i>Fit statistics</i>						
Standard-Errors	Category			IID		
Observations	1,105,697	227,979	132,240	222,481	332,907	190,090
Squared Correlation	0.190	0.215	0.192	0.185	0.184	0.177
Pseudo R ²	0.149	0.170	0.151	0.146	0.143	0.139
BIC	1,305,929.5	262,697.6	152,658.7	263,914.0	395,633.6	226,730.0

Notes: This table presents regression results analysing regression on sales using a logit model over the whole sample and 5 categories with a total of: 1,108,423 observations. The table presents the variable "Price quintile" as an ordinal categorical variable with reference the first quintile (the lowest prices). Quintiles are calculated on category and monthly basis. * p < 0.10, ** p < 0.05, *** p < 0.01.

marketplaces. The results underscore the importance of tailoring image strategies to specific product categories. For example, professional catalogue images are more suitable for

categories where buyers emphasize clarity and product detail, while real-person images perform better in segments where personalization enhances engagement. Additionally, the positive correlation between professional imagery and sales in higher price quintiles highlights the importance of investing in high-quality visuals for premium items to align with buyer expectations.

By providing evidence of these category-specific dynamics, the study extends the existing literature on visual presentation and trust in online marketplaces. The insights have practical implications for sellers and platforms seeking to optimize strategies to enhance buyer trust, engagement, and sales outcomes in the context of second-hand goods.

The variable capturing whether the garment's condition is disclosed *Condition Disclosed* is negatively associated with sales in several categories, including pants and jackets, which may indicate buyer scepticism or reduced trust when condition details are provided. User-related factors play a crucial role in predicting sales outcomes. The number of reviews at the time of purchase consistently shows a positive and significant association with sales across all categories, highlighting the importance of a strong reputation in influencing buyer decisions. Similarly, the number of likes on a listing emerges as a significant predictor of sales, underscoring the role of engagement and perceived popularity in enhancing a product's appeal to potential buyers. Both factors collectively emphasize the impact of user reputation and listing engagement in driving successful sales.

Brand-related factors, such as brand perception and the log of brand products, show nuanced effects. Brand perception positively influences sales across most categories, with the strongest effects seen in dresses and jackets. The log of brand products is positively associated with sales in the full sample but exhibits mixed effects when disaggregated by category, probably due to the reduction of size for brands when using individual categories.

The variables for Beauty and Person in Profile Picture⁵, reveal interesting patterns in the data. Beauty, which captures the aesthetic appeal of the user, consistently shows a small but significant negative association with sales across all categories. This suggests that higher beauty ratings, while visually appealing, may introduce scepticism among buyers or indicate products with less practical appeal. In contrast, the presence of a person in

⁵How beauty is calculated will be covered in detail in the next section

the seller's profile picture has a consistently positive and significant association with sales across all categories. This finding underscores the importance of trust and relatability in online marketplaces, as buyers may perceive sellers with personal profile pictures as more trustworthy or approachable, thereby increasing the likelihood of completing a purchase.

4.3. Does Beauty Matter?

Appearances were classified using CLIP, a neural network model developed by OpenAI that can associate images with descriptive text. Each profile picture was assigned an appearance score between 0 and 100, which were then divided into quintiles to create five distinct groups for analysis. The distribution of beauty scores appears to follow a normal distribution, as shown in Figures C.21 and C.22, both for unique users and generally across all users who post products on the platform. The variable *Beauty Category* was constructed by dividing the beauty scores into 10 equal intervals, each representing a 10-point range within the 0-100 scale. This categorization creates a straightforward way to group items based on their aesthetic appeal, with categories ranging from 0-10 (the lowest beauty) to 90-100 (the highest beauty). By using this categorical representation, the analysis captures the effect of varying levels of perceived beauty on sales outcomes while facilitating the interpretation of interactions with image type.

The results reveal a nuanced relationship between seller beauty, as measured by profile pictures, and sales outcomes, highlighting the importance of aligning visual cues with product presentation. Beauty alone exhibits a slightly negative association with sales across most categories, with significant effects observed for jackets, dresses, and the full sample. These findings suggest that higher beauty scores, when not complemented by suitable product visuals, may elicit buyer scepticism or signal inconsistency between the seller's appearance and the perceived quality of their products.

However, interactions between seller beauty and image type yield important insights. Beauty positively interacts with *Real Person Images* and *Professional Models*, indicating that sellers with high beauty scores can leverage personalized and professional-grade visuals to enhance sales outcomes. These effects are particularly pronounced in categories like dresses, where buyers prioritize visuals that emphasize fit and style. Conversely, in categories such as Pants, catalogue images paired with high-beauty sellers enhance buyer

perceptions of product quality and trustworthiness.

These findings underscore the importance of strategic alignment between seller attributes and image presentation. Sellers with high-beauty profile pictures should prioritize catalogue and professional-grade visuals to align with buyer expectations and mitigate scepticism. Real-person images, when used strategically in categories like Dresses, can enhance emotional engagement, particularly for sellers with high beauty scores. For sellers with lower beauty scores, focusing on authenticity cues through naturalistic product photos is recommended, especially in categories like jackets and pants, where clarity and trust signals play a critical role.

From a platform perspective, these results suggest opportunities to refine seller tools and recommendations. Platforms could employ AI-driven algorithms to assess profile pictures and suggest optimal image types for listings. Additionally, category-specific guidelines could be updated to reflect the complex interplay between seller beauty, product categories, and image presentation.

Finally, having a *Person in Profile Picture* consistently shows a positive and significant association with sales across all categories. This finding underscores the importance of seller trust and relatability in driving sales outcomes. Together, these results highlight the interplay between beauty, image type, and perceived professionalism in shaping buyer behaviour across different product categories.

5 Conclusion

This study reveals significant heterogeneity in the impact of visual presentation on sales performance across product categories in second-hand marketplaces. For categories such as pants and jackets, professional catalogue images significantly enhance sales likelihood, as buyers in these segments prioritize clarity and uniformity in product presentation. This finding aligns with signalling theory, where polished, professional images serve as credible indicators of product quality in environments characterized by information asymmetry.

In contrast, real-person images are particularly effective in categories like dresses, where demonstrating fit and style plays a crucial role in influencing buyer decisions. This suggests that personalized visual cues help buyers envision the product in use, reflecting prin-

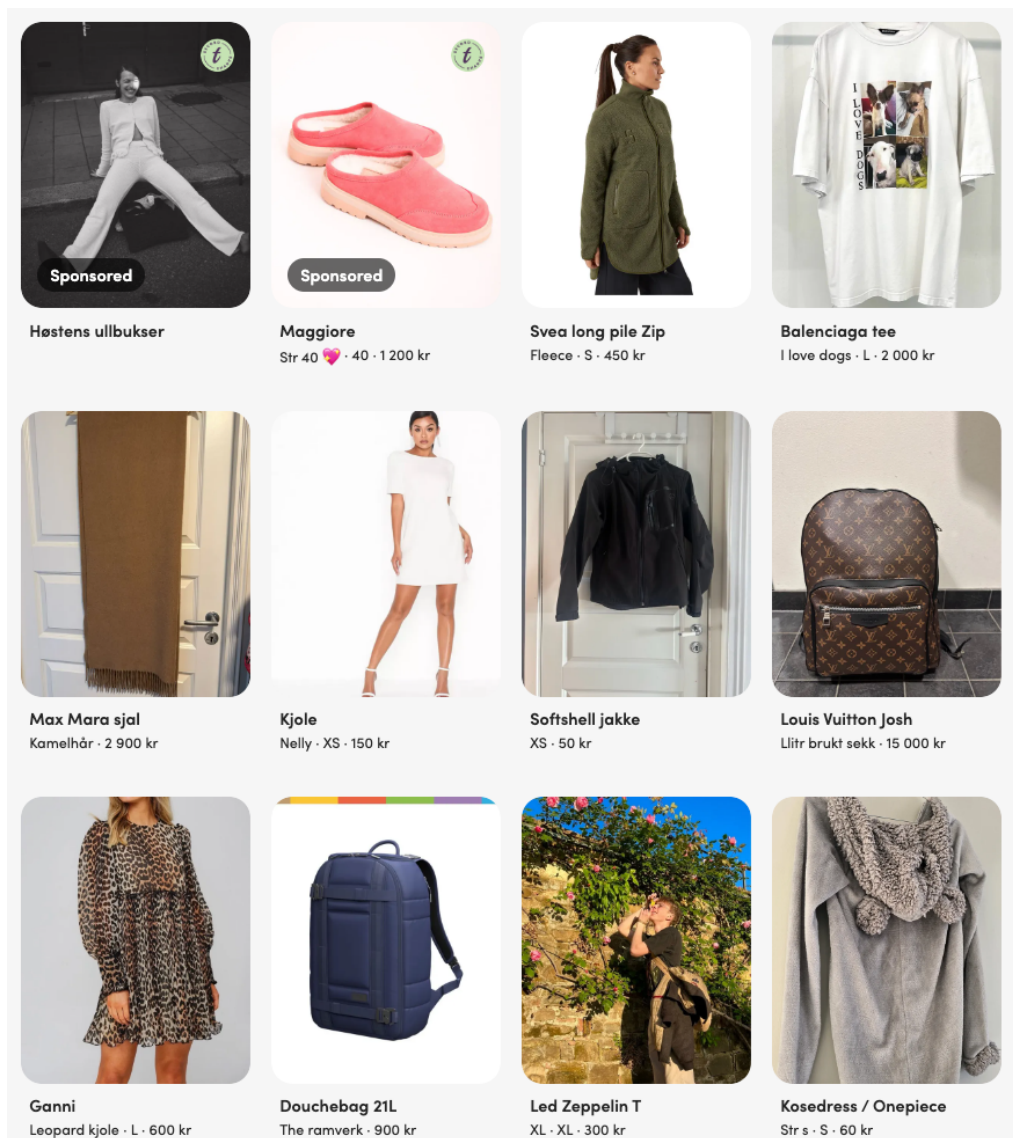
ciples of consumer engagement and emotional purchasing. However, the analysis also reveals that real-person images can negatively impact sales in categories such as sweaters and pants, where overly personalized imagery may distract buyers from focusing on the product itself.

These findings offer valuable insights for both sellers and platforms. Sellers can optimize sales performance by tailoring their visual strategies to specific product categories, using professional catalogue images for items like pants, sweaters, and jackets to highlight product details, and real-person images for dresses to enhance engagement through fit and style visualization. For high-value items, sellers should invest in professional imagery to meet the heightened expectations of buyers for premium products.

Platforms can leverage these findings by incorporating tools and features that guide sellers in selecting the most effective image types based on product category and price. Additionally, integrating visual presentation quality into reputation systems could strengthen trust metrics, fostering a more reliable and engaging marketplace environment.

By extending existing literature on visual presentation in online marketplaces, this study provides robust evidence of the nuanced ways in which image types interact with product characteristics in second-hand contexts. These insights hold practical implications for enhancing trust, engagement, and sales outcomes, benefiting both sellers and platforms while enriching the overall marketplace experience.

Figure 3.1. Website interface



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Conclusion

This thesis examines the influence of digital platforms on economic behaviour across three interconnected areas: strategic voting in competitive settings, the impact of sociopolitical events on digital goods consumption, and user behaviour in online marketplaces. The common thread is the role of digital platforms. In the first chapter, platform data is used to assess genuine musical tastes across nations. The second chapter investigates how a widely used platform reflects shifts in consumption patterns following a political and social event. The third chapter focuses on online second-hand marketplaces, exploring how these digital “flea market” are redefining product advertising and influencing pricing and purchasing behaviour. These topics are increasingly relevant, as they have the potential to reshape how retailers approach product lifecycles and sustainability in the coming years.

Each chapter is independent and focuses on a clear research question.

In Chapter 1, we examine strategic voting in large-scale (televote) and small-scale (jury) elections within a positional voting system, using data from the Eurovision Song Contest and Spotify. By analysing votes and Spotify data, we aimed to explore whether voters made decisions based on genuine musical preferences or strategic motives. The findings reveal that strategic voting does occur, predominantly influenced by contest-specific events, such as the semifinals, and less on actual characteristics of the song. Spotify charts data, used as an external metric, showed no significant impact on final voting outcomes. However, in cases where no prior voting data exists, such as for the Big 5⁶, that automatically qualify for the final, Spotify data can provide a more accurate reflection of preferences. This indicates that in the absence of internal contest information, voters may lean more on personal taste. In contrast, when internal contest dynamics, such as semifinal results, are available, voters are more likely to engage in strategic voting to favour their own country, especially by penalizing close competitors.

In Chapter 2, we explore the phenomenon of political consumerism by examining how

⁶France, Germany, Italy, Spain, and the United Kingdom

the appointment of Justice Brett Kavanaugh to the US Supreme Court influenced digital music consumption patterns. The heightened media attention on the alleged sexual misconduct, ignited widespread public discourse on gender equality and women's rights. In this chapter, we investigated whether this political event prompted consumers to alter their music listening habits as a form of socio-political expression. With a difference-in-difference analysing we observed a notable increase in the consumption of music performed by female artists in the United States with respect to their male counterpart of about 16%. This shift suggests that consumers engaged in "boycotting", intentionally supporting female artists as a response to the political climate. The findings provide empirical evidence that significant political events can catalyse changes in consumer behaviour.

This chapter contributes to the literature on political consumerism by demonstrating how consumption is becoming more an instrument "to vote" with their wallet and express their political and social values. The use of digital platforms amplifies the impact of such consumer activism due to their broad reach and the ease with which users can access and share content. For businesses and marketers, these insights underscore the importance of understanding the socio-political contexts that influence consumer preferences and the potential for political events to affect market dynamics. Moreover, the study highlights the role of digital platforms not only as passive channels for consumption but also as active arenas where societal issues are reflected and amplified. This has implications for platform governance and the responsibility of digital service providers in navigating the intersection of commerce and socio-political discourse.

In Chapter 3, I focus on second-hand marketplaces, with particular attention to second-hand clothing platforms such as Vinted. The study explores the factors influencing sales and pricing, emphasizing the impact of visual elements in postings. Specifically, it examines how the subject of the image, whether clothing alone, a real person, a catalogue image, or a professional model, affects user engagement, sales probability, and pricing strategies. My research showed that listings with more professionally looking images have higher prices and higher sale probability compared to those without people in the picture or with non-professional visuals. These findings emphasize the critical role of visuals in online marketplace: buyers cannot physically inspect products before purchase but still prefer a professional setting even in a resale context. As already proven by the literature, profile

picture serve as a tool for reducing uncertainty and building trust between buyers and sellers. For sellers, increasing the effort in looking for a professional or recreate professional looking pictures can enhance the attractiveness of their listings, leading to improved sales outcomes. The study contributes to understanding the factors that affect transaction outcomes in peer-to-peer marketplaces by highlighting how visual elements, especially image presentation, shape consumer behaviour. It offers practical insights for sellers aiming to optimize their strategies and for platform designers seeking to enhance user experience, while stressing the importance of preserving privacy by discouraging the use of images that do little to drive sales. Improved visual information reduces information asymmetry, lowers return rates, and boosts buyer confidence, leading to more efficient market transactions.

The research presented in this thesis demonstrates how digital platforms serve as versatile tools for analysing both economic and social behaviour. In a world where these platforms are deeply integrated into everyday life, their impact on market dynamics and user interactions is critical. Digital platforms not only offer user-friendly interfaces but also provide rich data that help answer long-standing questions across multiple fields. At the same time, the widespread use of digital platforms raises important regulatory concerns. Their data-gathering capabilities and influence can concentrate power with platform owners, creating risks of market dominance and user exploitation. Therefore, proper governance and balanced regulation are essential to ensure that the benefits of innovation do not come at the expense of fairness, transparency, or user rights.

A Chapter 1: Additional Tables

Table A.1. Eurovision final-based *Distance_Past*

Dependent Variable:	Points						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.045 (0.034)	0.081* (0.047)	0.037 (0.054)	-0.382*** (0.054)	-0.340*** (0.091)	-0.186 (0.140)	-0.494*** (0.117)
Above_Past		-0.059 (0.054)	0.030 (0.077)	0.076 (0.073)	0.038 (0.122)	0.121 (0.187)	-0.045 (0.156)
Distance_Past	-0.214 (0.201)	-0.238 (0.216)	0.109 (0.305)	-0.245 (0.288)	-0.137 (0.378)	-0.100 (0.578)	-0.173 (0.485)
Distance_Past:Above_Past			-0.696 (0.433)	-3.482*** (0.422)	-2.854*** (0.559)	-2.571*** (0.854)	-3.138*** (0.717)
Past				0.181*** (0.007)	0.145*** (0.010)	0.095*** (0.015)	0.196*** (0.013)
Voters Years	Mean	Mean	Mean	Mean	All ≥ 2016	Jury ≥ 2016	Telev. ≥ 2016
Observations	5378	4778	4778	4778	4728	2364	2364
R^2	0.000	0.001	0.001	0.115	0.043	0.018	0.089
Adjusted R^2	0.000	0.000	0.000	0.114	0.042	0.016	0.088

Notes: Estimation of Equation (1.1) for different specifications of *vote*. For better readability, *distance* is expressed in thousands of points (while *vote* is expressed in points). Years 2008–2023 except 2020. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.2. Effect of position within Eurovision ranking

Dependent Variable:	Points						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	-0.264** (0.112)	-0.481 (0.398)	-0.387 (0.335)	-0.478*** (0.058)	-0.622*** (0.131)	-0.667*** (0.182)	-0.577*** (0.156)
Distance	2.471* (1.302)	6.885** (3.207)	-1.962 (2.699)	-0.047 (0.272)	0.637 (0.454)	0.976 (0.633)	0.299 (0.542)
Distance:Position	-0.028 (0.174)	-0.668 (0.524)	0.682 (0.441)	0.040** (0.019)	0.013 (0.029)	-0.003 (0.041)	0.029 (0.035)
Past	0.467*** (0.021)	0.514*** (0.066)	0.650*** (0.055)	0.335*** (0.010)	0.317*** (0.022)	0.249*** (0.030)	0.385*** (0.026)
Position	-0.014 (0.012)	0.055 (0.061)	-0.039 (0.052)	0.000 (0.004)	0.009 (0.008)	0.017 (0.011)	0.001 (0.009)
Distance	Semif.	Semif.	Semif.	Final	Final	Final	Final
Voters	Mean	Jury	Telev.	Mean	Mean	Jury	Telev.
Years		≥ 2016	≥ 2016		≥ 2016	≥ 2016	≥ 2016
Observations	2520	1080	1080	8902	3850	3850	3850
R^2	0.163	0.061	0.117	0.104	0.056	0.020	0.056
Adjusted R^2	0.162	0.058	0.114	0.104	0.055	0.019	0.055

Notes: Estimation of Equation (1.1) interacting *distance* with the position in the rankings of the song that receives the vote. For better readability, *distance* is expressed in thousands of points (while *vote* is expressed in points). Years 2008–2023 except 2020. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A.3. Example of votes breakdown in the final of 2022

Voter Country	Receiving Country	Televote Rank	Jury Rank	Jury Points	Televote Points	j1	j2	j3	j4	j5
Albania	Armenia	17	7	4	0	8	5	9	9	10
Albania	Australia	21	13	0	0	12	13	23	16	7
Albania	Azerbaijan	18	8	3	0	6	17	17	12	6
Albania	Belgium	14	9	2	0	13	7	8	11	16
Albania	Czech Republic	24	21	0	0	19	14	21	20	18
Albania	Estonia	6	12	0	5	10	8	24	17	12
Albania	Finland	9	16	0	2	21	19	5	19	20
Albania	France	22	24	0	0	23	23	18	23	21
Albania	Germany	20	17	0	0	9	16	16	10	19
Albania	Greece	1	11	0	12	15	10	19	8	8
Albania	Iceland	25	14	0	0	14	21	7	13	14
Albania	Italy	3	1	12	8	1	2	2	1	2
Albania	Lithuania	19	15	0	0	16	18	6	14	23
Albania	Moldova	10	23	0	0	25	22	14	22	24
Albania	Netherlands	5	5	6	6	5	6	11	3	3
Albania	Norway	16	20	0	0	17	20	15	18	15
Albania	Poland	13	19	0	0	11	15	25	21	17
Albania	Portugal	15	10	0	0	20	12	13	5	11
Albania	Romania	12	25	0	0	18	25	22	25	22
Albania	Serbia	8	22	0	3	24	24	12	24	25
Albania	Spain	4	6	5	7	3	9	10	7	9
Albania	Sweden	11	3	8	0	7	1	4	4	5
Albania	Switzerland	23	18	0	0	22	11	20	15	13
Albania	Ukraine	2	4	7	10	4	3	3	6	4
Albania	United Kingdom	7	2	10	4	2	4	1	2	1

Notes: This table provides a detailed breakdown of the voting in the Eurovision 2022 final. Each row represents a voting country's allocation of points to various receiving countries. Columns include the Televote rank, jury rank, jury points, televote points, and individual jury member votes (j1 to j5).

Table A.4. Descriptive Statistics of Eurovision songs between 2008 and 2023

Variable	Mean	SD
Danceability	0.56	0.14
Energy	0.70	0.18
Key	5.40	3.58
Loudness	-5.92	2.17
Mode	0.47	0.50
Speechiness	0.06	0.05
Acousticness	0.21	0.24
Instrumentalness	0.00	0.03
Liveness	0.19	0.13
Valence	0.46	0.22
Tempo (BPM)	121.80	27.18
Time Signature	3.92	0.33
Is Explicit	0.01	0.11
Duration (m:ss)	3.23	0.14
Female Percentage	0.45	0.48
Size of Group	1.64	1.37

Notes: The table reports descriptive statistics for key variables of Eurovision songs between 2008 and 2023. SD stands for standard deviation. *Number of observations:* 609

Table A.5. Charts sample for Austria on 1st May 2023

rank	Artist	Track Name	Procucer	Peak Rank	Previous Rank	Days on Chart	Streams
1	David Kushner	Daylight	Miserable Music Group, LLC	1	1	18	36366
2	Bonez MC, Gzuz	Cinnamon Roll	187 Strassenbande	1	2	11	28243
3	Udo Lindenberg, Apache 207	Komet	Warner Music Central Europe	2	3	102	25086
4	RAF Camora, Luciano	All Night	Indipendenza	1	4	33	24939
5	Eminem	Mockingbird	Aftermath	2	6	205	23492
...	...	...	...	...	...	...	...
196	Stephen Sanchez, Em Beihold	Until I Found You	Republic Records	26	-1	117	5298
197	Rihanna, Calvin Harris	We Found Love	Def Jam Recordings	67	179	65	5295
198	Linkin Park	In the End	Warner Records	6	-1	894	5281
199	t-low, Miksu / Macloud	We Made It	t-low	1	-1	354	5276
200	Pitbull, Kesha	Timber (feat. Ke\$ha)	Mr.305/Polo Grounds Music/RCA Records	69	180	374	5274

Notes: This table is an example of the daily Spotify charts, in this case of Austria's streaming charts on May 1, 2023, ranking tracks by popularity. It includes artist names, track titles, production credits, and performance metrics like peak rank, prior rank, duration on chart, and total streams, reflecting the dynamic listening preferences.

Table A.6. Summary Statistics - Votes in the ESC Final from 2008 to 2023

Country	Times voted	Times non-zero voted	Points Received	Mean Points Received	Non Zero Mean Points Received	# in the Final
Albania	870	181	545	1.50	4.70	9
Armenia	754	151	932	2.40	4.80	10
Australia	464	110	867	3.10	4.20	7
Austria	696	154	707	2.60	4.60	7
Azerbaijan	870	179	1526	3.00	5.50	13
Belarus	696	140	166	0.90	3.80	5
Belgium	870	177	863	2.80	4.50	8
Bulgaria	638	141	629	3.90	4.80	4
Croatia	754	162	249	1.20	3.10	5
Cyprus	812	170	567	1.60	4.20	9
Czech Republic	580	139	258	1.60	3.00	4
Denmark	870	177	1004	2.50	5.00	10
Estonia	870	179	733	2.00	4.30	9
Finland	870	184	649	1.80	4.80	9
France	870	185	1003	1.70	3.80	15
Georgia	812	175	482	2.00	5.40	6
Germany	870	182	773	1.30	4.90	15
Greece	870	181	1140	2.40	5.40	12
Hungary	638	135	518	1.60	3.80	8
Iceland	870	174	850	2.20	5.10	10
Ireland	870	185	263	1.30	4.20	5
Israel	870	178	935	2.40	4.40	10
Italy	696	157	1931	4.10	5.60	12
Latvia	870	182	335	2.70	4.80	3
Lithuania	870	176	631	1.60	3.90	10
Malta	870	181	481	1.80	3.80	7
Moldova	870	181	868	2.20	4.40	10
Montenegro	638	135	81	1.10	7.40	2
Netherlands	870	181	904	2.90	4.70	8
North Macedonia	812	167	223	2.80	4.90	2
Norway	870	177	1569	3.10	4.70	13
Poland	754	170	354	1.30	3.00	7
Portugal	754	161	777	2.50	5.40	8
Romania	812	170	740	1.90	4.60	10
Russia	696	140	1887	4.30	6.20	11
San Marino	754	161	77	0.70	2.70	3
Serbia	812	173	964	2.20	5.20	11
Slovenia	870	185	267	1.10	3.20	6
Spain	870	173	770	1.30	4.00	15
Sweden	870	179	2450	4.40	5.90	14
Switzerland	870	182	566	2.50	4.20	6
Ukraine	754	158	1931	3.80	5.90	13
United Kingdom	870	186	738	1.20	4.10	15

Notes: This table summarizes voting patterns for the ESC finals from 2008 to 2023. It details each country's total and non-zero vote counts, points received, mean and non-zero mean points. The data provides insights into the trends and performances of participating countries. The statistics cover the number of times each country participated in the final and reflect total, average, and non-zero average scores. Source: [Flecht \(2024\)](#).

Table A.7. Voting Matrix for the 2008 Final

rcv_cty vtn_cty	Albania	Armenia	Azerbaijan	...	...	...	France	United Kingdom	Georgia
Andorra	0.0	0.0	7.0	...	...	...	3.0	0.0	0.0
Albania	NaN	2.0	0.0	...	...	...	0.0	0.0	0.0
Armenia	0.0	NaN	0.0	...	...	...	4.0	0.0	10.0
...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...
San Marino	3.0	8.0	0.0	...	...	...	0.0	6.0	0.0
Turkey	1.0	10.0	12.0	...	...	...	0.0	0.0	4.0
Ukraine	0.0	7.0	10.0	...	...	...	0.0	0.0	8.0

Notes: This matrix represents the voting patterns during the 2008 Eurovision Song Contest final. Each cell shows the number of points awarded by the voting country (row) to the receiving country (column). “NaN” indicates instances where a country could not vote for itself.

Table A.8. Popularity of Eurovision in Country: Number of Eurovision songs that Country have in its charts

Country	Min	Max	Average
Austria	1.00	6.00	3.17
Australia	1.00	1.00	1.00
Belgium	2.00	16.00	8.67
Bulgaria	1.00	3.00	1.40
Switzerland	1.00	5.00	2.80
Czech Republic	1.00	4.00	2.40
Germany	2.00	4.00	2.67
Denmark	1.00	8.00	3.67
Estonia	4.00	23.00	14.17
Spain	1.00	8.00	4.50
Finland	2.00	37.00	17.50
France	1.00	2.00	1.40
United Kingdom	1.00	6.00	3.50
Greece	3.00	12.00	7.17
Hungary	2.00	10.00	5.50
Ireland	2.00	5.00	3.00
Israel	3.00	13.00	7.25
Iceland	24.00	40.00	33.83
Italy	1.00	3.00	1.67
Lithuania	8.00	37.00	23.67
Latvia	1.00	16.00	8.60
Netherlands	3.00	23.00	9.17
Norway	5.00	24.00	14.50
Poland	1.00	10.00	4.60
Portugal	1.00	4.00	2.40
Romania	1.00	3.00	2.20
Sweden	11.00	24.00	17.17
Ukraine	3.00	6.00	4.33

Notes: This table presents the popularity of songs from various countries in international markets, as reflected in Spotify Charts. It shows the minimum (Min), maximum (Max), and average (Average) Number of countries where songs from each listed Country have appeared in the charts.

Table A.9. Song popularity in other countries (how many countries have a Country song in their chart)

Country	Min	Max	Average	Country	Min	Max	Average
Albania	0.00	3.00	1.00	Italy	1.00	22.00	11.00
Armenia	0.00	7.00	2.00	Lithuania	0.00	9.00	5.00
Austria	0.00	13.00	6.00	Latvia	0.00	4.00	2.00
Australia	2.00	7.00	4.00	Moldova	0.00	9.00	4.00
Azerbaijan	0.00	10.00	4.00	Montenegro	0.00	1.00	0.00
Bosnia	0.00	0.00	0.00	North Macedonia	0.00	5.00	1.00
Belgium	2.00	14.00	7.00	Malta	0.00	10.00	4.00
Bulgaria	0.00	11.00	4.00	Netherlands	3.00	17.00	7.00
Belarus	0.00	2.00	0.00	Norway	0.00	25.00	11.00
Switzerland	0.00	12.00	6.00	Poland	1.00	11.00	4.00
Cyprus	2.00	19.00	8.00	Portugal	0.00	10.00	5.00
Czech Republic	0.00	15.00	7.00	Romania	0.00	8.00	2.00
Germany	0.00	8.00	4.00	Serbia	0.00	7.00	2.00
Denmark	2.00	5.00	3.00	Russia	0.00	10.00	2.00
Estonia	2.00	6.00	3.00	Sweden	9.00	28.00	13.00
Spain	2.00	11.00	4.00	Slovenia	1.00	8.00	3.00
Finland	0.00	25.00	9.00	San Marino	0.00	7.00	2.00
France	2.00	11.00	7.00	Turkey	0.00	0.00	0.00
United Kingdom	1.00	10.00	5.00	Ukraine	0.00	20.00	8.00
Georgia	0.00	6.00	2.00				
Greece	2.00	9.00	4.00				
Croatia	0.00	9.00	4.00				
Hungary	0.00	6.00	2.00				
Ireland	0.00	4.00	2.00				
Israel	2.00	17.00	8.00				
Iceland	1.00	12.00	4.00				

Notes: This table presents the popularity of songs from various countries in international markets, as reflected in Spotify Charts. It shows the minimum (Min), maximum (Max), and average (Average) Number of countries where songs from each listed Country have appeared in the charts.

Table A.10. Voting Systems adopted in the Eurovision

Year	Points Awarded	Voting Method
1956	$(10-1) \times 2$	Two jurors per country rated each song on a scale of 1 to 10 points.
1957–1961	10–1	Ten-member juries distributed 10 points among their favourite songs.
1962	3–1	Ten-member juries awarded points to their three favourite songs.
1963	5–1	1962: Twenty-member juries awarded points to their five favourite songs.
1964–1966	5, 3, 1 / 6, 3 / 9	Ten-member juries distributed 9 points in three possible ways.
1967–1970	10–1	Ten-member juries distributed 10 points among their favourite songs.
1971–1973	10–2	Two-member juries (one aged over 25 and the other under 25, with at least 10 years between their ages) rated songs between 1 and 5 points.
1974	10–1	Ten-member juries distributed 10 points among their favourite songs.
1975–1996	12, 10, 8–1	All countries had at least eleven jury members that would award points to their top ten songs.
1997		Twenty countries had jury members and five countries used televote to decide which songs would get points.
1998–2000		Televoting used in all countries.
2001–2002		Choice between full televoting and mixed system.
2003		Telephone/SMS voting in all countries.
2004–2008; 2009 (semi-finals)		Televoting and/or SMS-voting used.
2009 (final); 2010–2012		All countries use televoting and/or SMS-voting (50%) and five-member juries (50%).
2013–2015		The jurors and televoting each rank all the competing entries.
2016–2017	$(12, 10, 8-1) \times 2$	The jury and the televote each award an independent set of points. First the jury points are announced and then the televoting points are calculated together before being added to the jury points, effectively doubling the points which can be awarded in total.
2018–2022	12, 10, 8–1 (semi-finals) $(12, 10, 8-1) \times 2$ (final)	The same as in 2016–17, but the points from a country's jury are now calculated using an exponential weight model.
2023		Semi-finals: only televote. Final: independent jury and televote points.

Notes: This table provides a historical overview of the Eurovision Song Contest's voting system from 1956 to 2023. It details the points awarded each year and the voting methods, illustrating the process's evolution. The table encompasses various voting methods, including jury-based, televote, and mixed systems, reflecting changes in technology and participation over the decades.

B Chapter 2: Additional Tables and figures

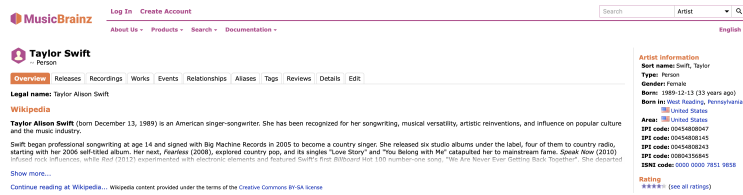


Figure B.1. Screenshot of a MusicBrainz Artist Webpage (Taylor Swift)

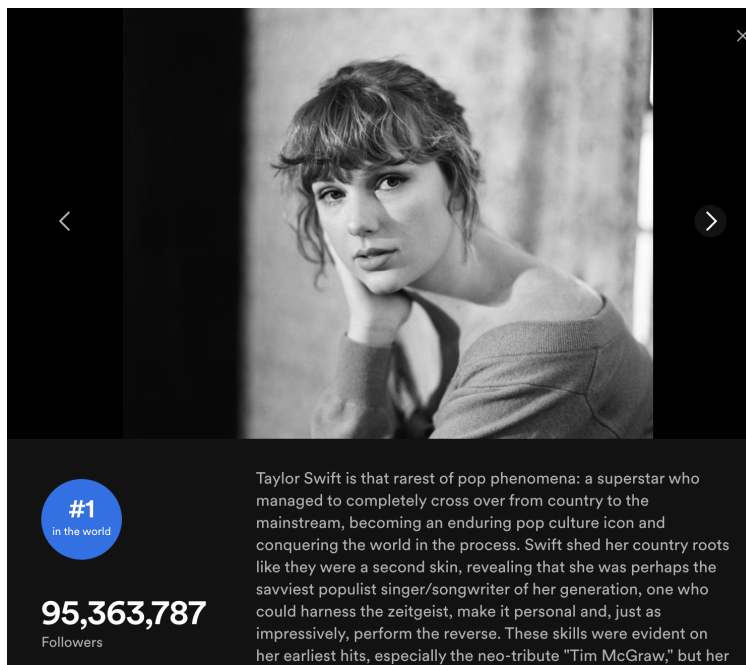
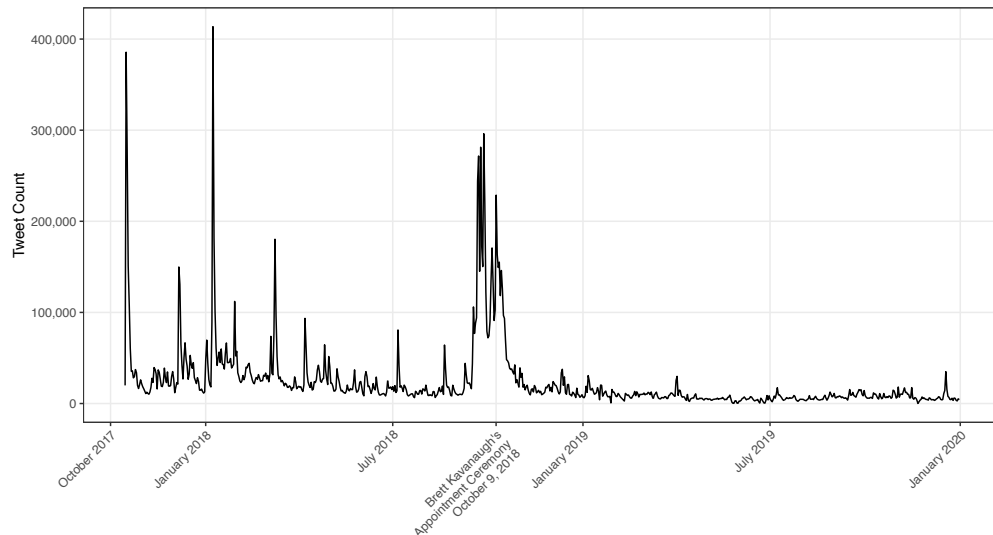


Figure B.2. Screenshot of a Spotify Artist Webpage (Taylor Swift)

Figure B.3. #MeToo Tweet Count over Time



Notes: This figure illustrates the daily count of tweets containing the #MeToo hashtag from 2017 to January 2020, sourced from the public Harvard Dataverse ([Maiorana, Morales Henry and Weintraub, 2023](#)). Three spikes can be seen: the first in October 2017 with Alyssa Milano's tweet, the second in January 2018 related to Oprah Winfrey's speech at the Golden Globes, and the third and longer corresponding to Brett Kavanaugh's nomination period.

Figure B.4. Share of Weekly Streams in the Spotify Top 200 US Spotify Charts for Female, and Male Artists and Groups from January 2018 to January 2020

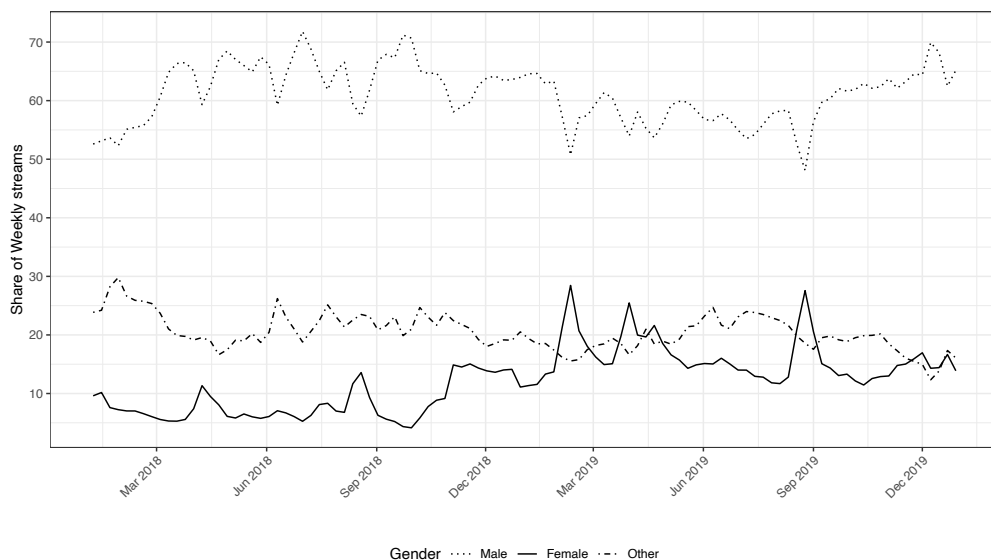
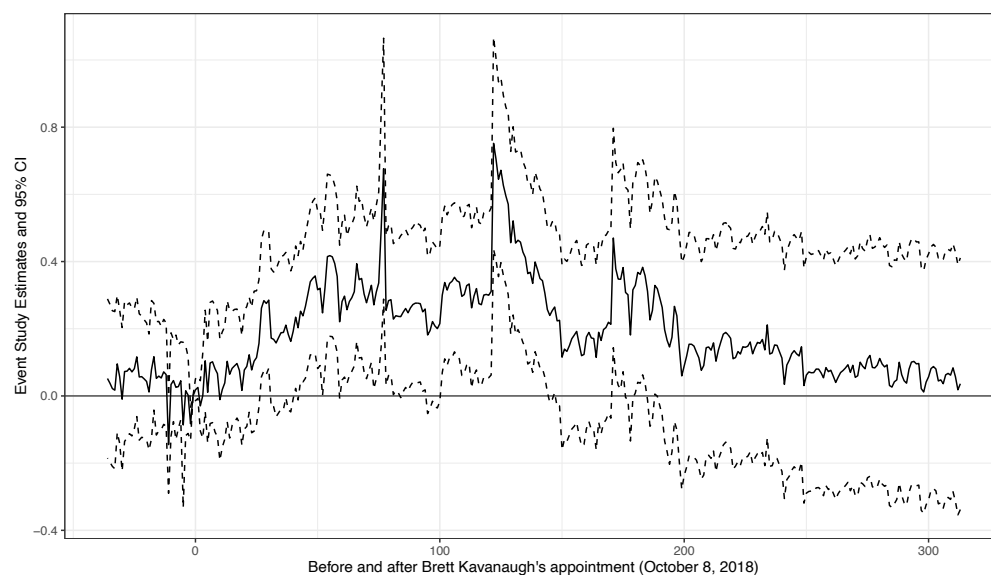


Table B.1. Summary Statistics - Songs by Female Artists and Groups in US

	Female		Groups		Difference	
	Mean	SD	Mean	SD	Δ	P-value
Charts						
Days on Chart	136	144	78	76	58	0.00
Chart Rank	104	59	101	58	3	0.03
Week of Release	0.11	0.32	0.04	0.19	0.08	0.00
Streams	410 344.93	251 351.92	449 715.08	386 390.24	-39 370.15	0.00
Artists						
Artist Followers	20 672 179	20 682 732	51 544 874	40 983 042	-30 872 695	0.00
Song Characteristics						
Song Duration (Seconds)	222	50	203	27	19	0.00
Is Explicit	0.48	0.5	0.32	0.46	0.16	0.00
Major Record Label	0.62	0.49	0.72	0.45	-0.1	0.00
Is Sexist	0.39	0.49	0.18	0.38	0.22	0.00
Is Single Release	0.39	0.49	0.56	0.5	-0.17	0.00
Acousticness	0.18	0.2	0.3	0.3	-0.12	0.00
Song Features						
Danceability	0.69	0.14	0.62	0.13	0.07	0.00
Energy	0.66	0.15	0.58	0.17	0.08	0.00
Musical Mode	0.64	0.48	0.6	0.49	0.05	0.00
Speechiness	0.13	0.12	0.08	0.06	0.05	0.00
Tempo (BPM)	123.08	30.47	119.21	28.2	3.87	0.00
Time Signature	4	0.22	3.9	0.3	0.09	0.00
Valence	0.48	0.2	0.38	0.17	0.1	0.00
Number of observations:	2,120		1,634		486	

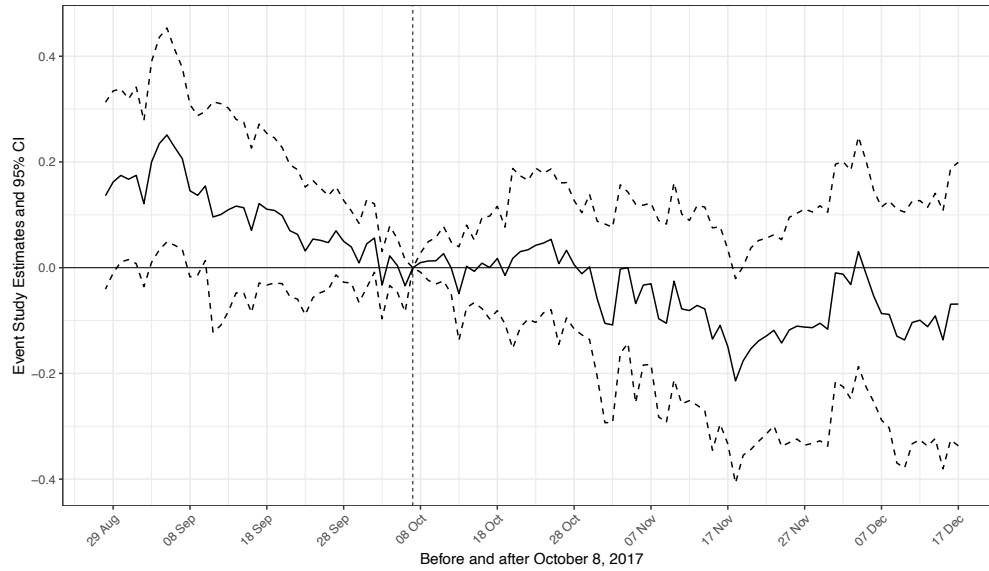
Notes: The table shows summary statistics about songs present in the Spotify top 200 us billboard between September 03, 2 018 and December 23, 2 018. Comparisons made between 57 (4) songs by female and 90 songs from groups. Gender identification based on publicly available data on MusicBrainz, Spotify, or Wikipedia.

Figure B.5. Event Study: $\log(\text{streams}_{it})$ - Songs by Female and Male Artists (Longer Time Window)



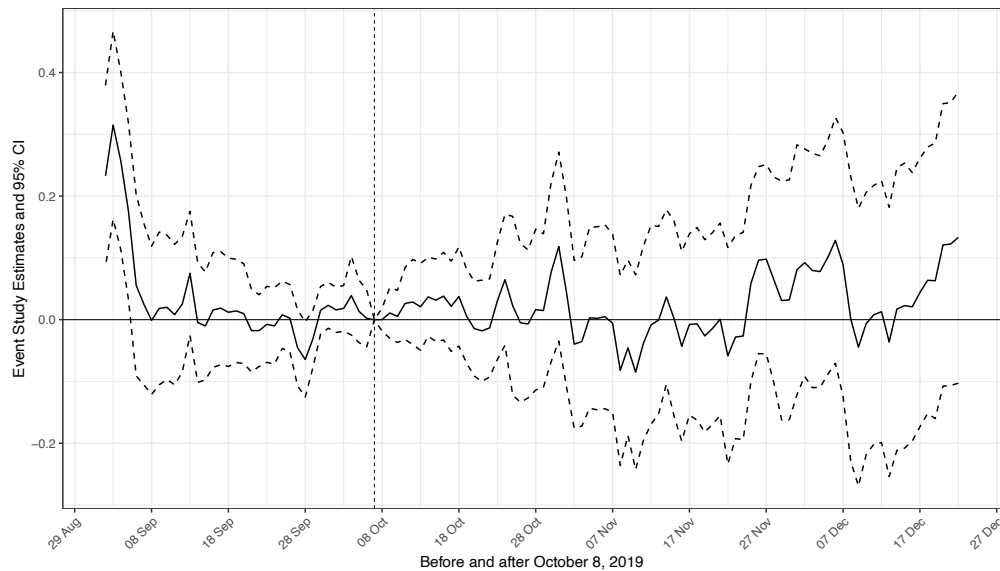
Notes: In line with Equation 2.2, $\log(\text{streams}_{it})$ is regressed on song fixed effect and on the products between Female_i and a full set of dummy variables for each day from September 3, 2018, to July 9, 2019. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 8, 2018, is normalized to 0. The sample includes songs in the US Top 200 Spotify Charts. Standard Errors (5%) are clustered at song level.

Figure B.6. Placebo Event Study: $\log(\text{streams}_{it})$ - Songs by Female and Male Artists in 2017



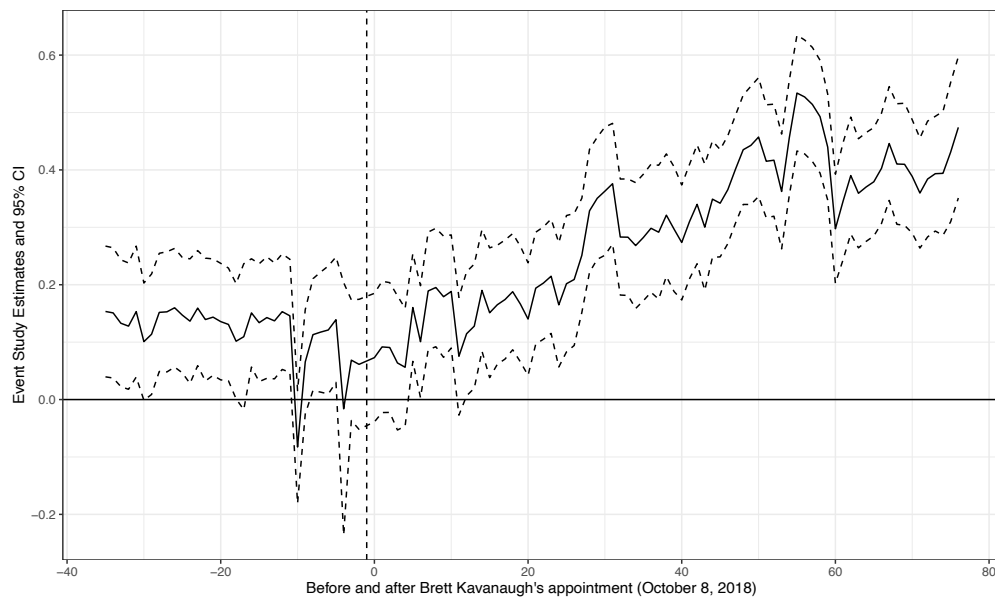
Notes: In line with Equation 2.2, $\log(\text{streams}_{it})$ is regressed on song fixed effect and on the products between Female_i and a full set of dummy variables for each day from September 3, 2017, to December 23, 2017. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 8, 2017, is normalized to 0. The sample includes songs in the US Top 200 Spotify Charts. Standard Errors (5%) are clustered at song level.

Figure B.7. Placebo Event Study: $\log(\text{streams}_{it})$ - Songs by Female and Male Artists in 2019



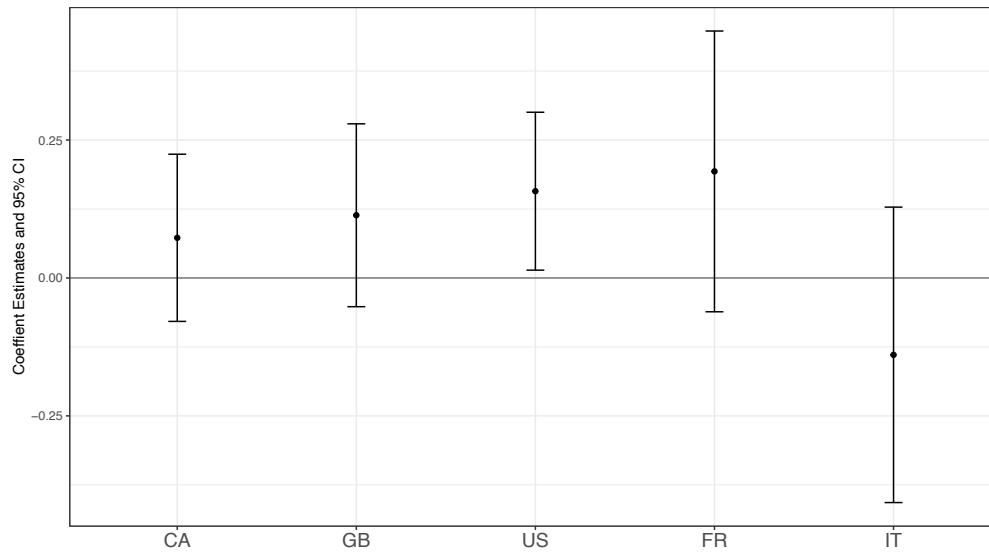
Notes: In line with Equation 2.2, $\log(\text{streams}_{it})$ is regressed on song fixed effect and on the products between Female_i and a full set of dummy variables for each day from September 3, 2019, to December 23, 2019. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 8, 2019, is normalized to 0. The sample includes songs in the US Top 200 Spotify Charts. Standard Errors (5%) are clustered at song level.

Figure B.8. Bootstrapped Event Study of $\log(\text{streams}_{it})$: Comparison of Songs by Female and Male



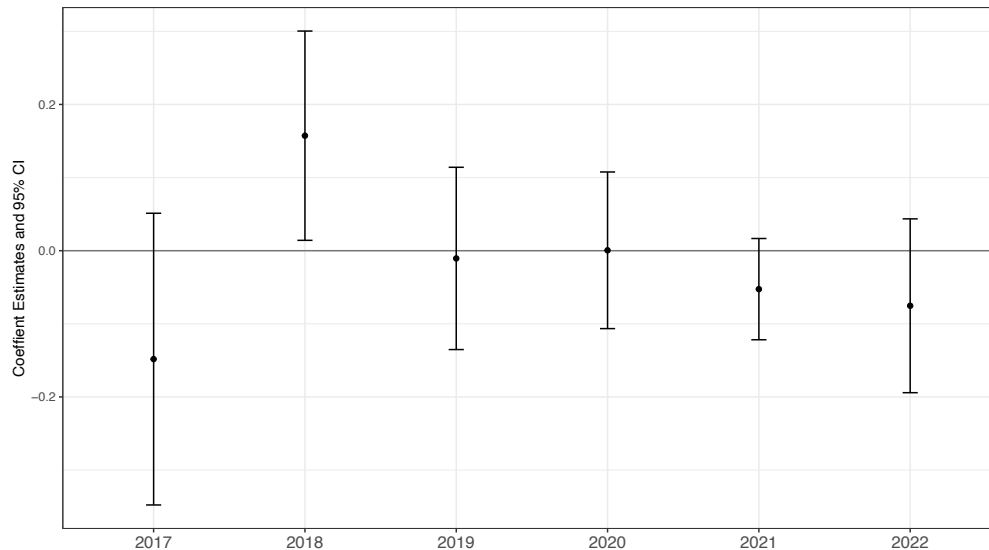
Notes: To ensure robustness in the event study analysis, we conducted bootstrapping by randomly removing 500 songs performed by female artists from the sample. This process was repeated 1,000 times.

Figure B.9. Event Study: $\log(\text{streams}_{it})$ - Songs by Female and Male Artists by Country



Notes: As an additional robustness check, we estimate the Difference-in-Differences regression described in Equation 2.1, incorporating data from Canada (CA), Great Britain (GB), the United States (US), France (FR), and Italy (IT). The coefficients, along with their corresponding 95% confidence intervals, are displayed for each country-specific estimate. Standard errors are clustered at the song level to ensure robust inference. This approach allows us to examine the consistency of the treatment effects across different geographical contexts.

Figure B.10. Event Study: $\log(\text{streams}_{it})$ - Songs by Female and Male Artists by Year



Notes: As an additional robustness check, we estimate the Difference-in-Differences regression described in Equation 2.1, stratifying the analysis by year in the US. The coefficients, along with their corresponding 95% confidence intervals, are displayed for each yearly estimate. Standard errors are clustered at the song level to ensure robust inference. This approach allows us to assess the stability of the treatment effects over time.

Figure B.11. Share of Weekly Presence of Female, and Male Artists and Groups in the Spotify Top 200 US Spotify Charts

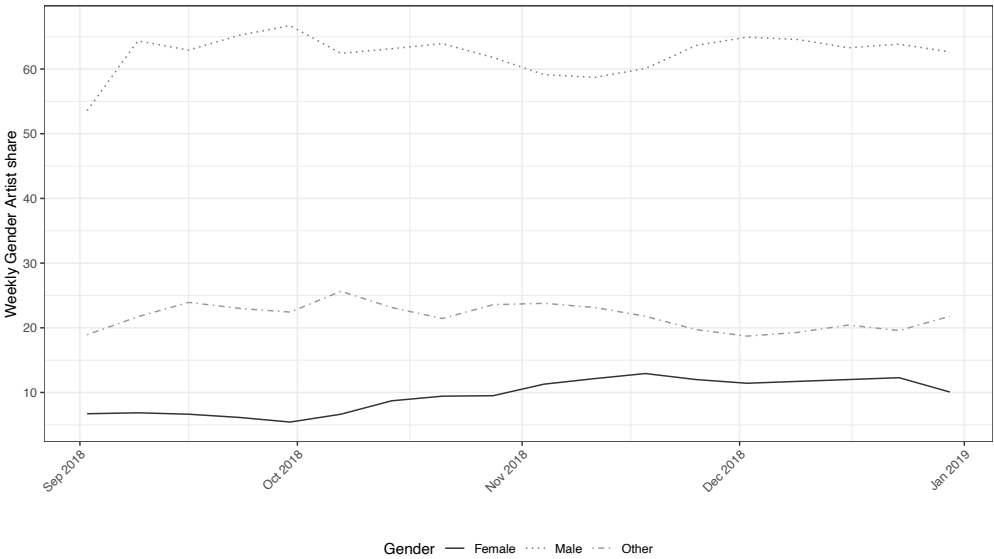
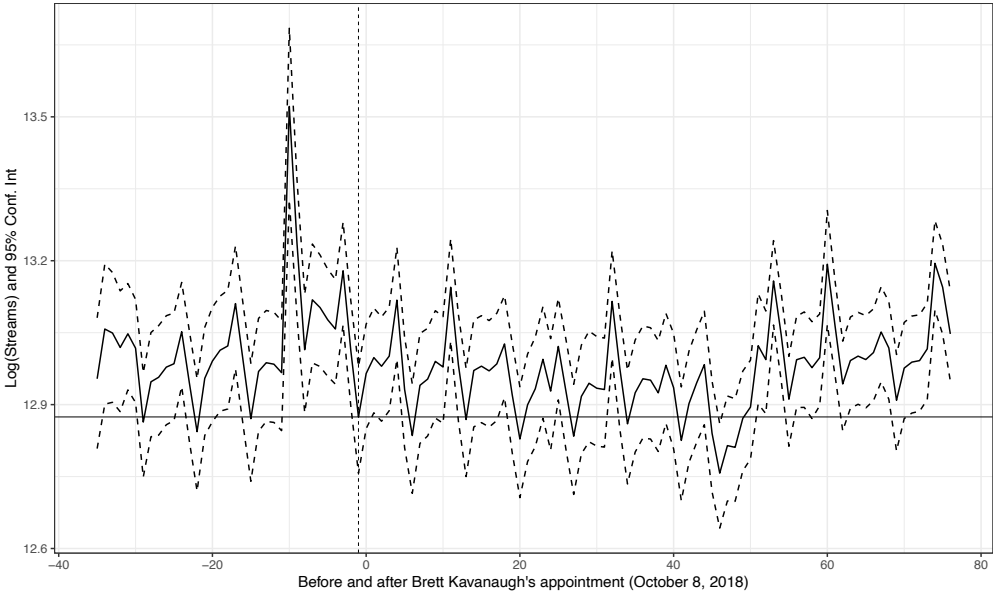
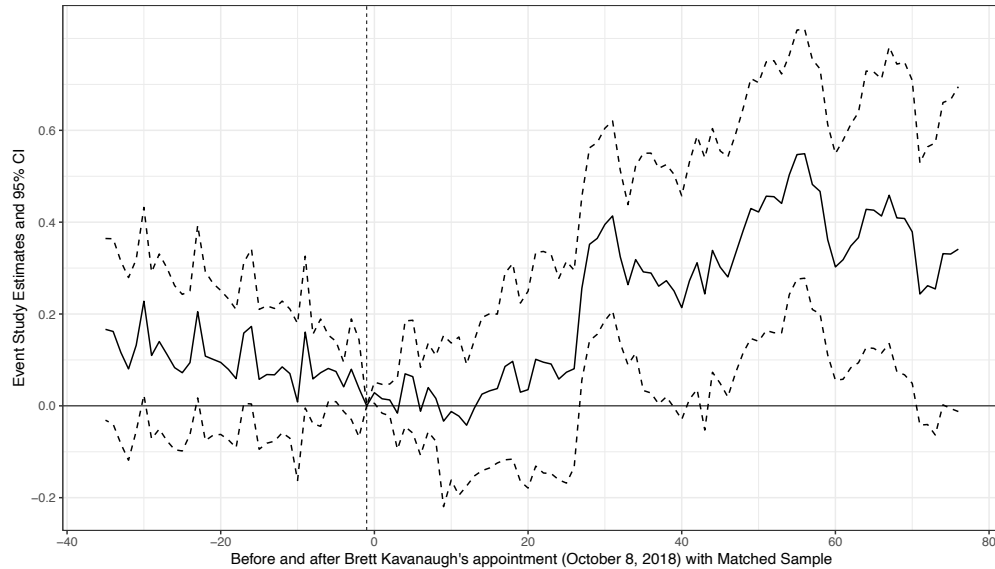


Figure B.12. Average $\log(\text{streams}_{it})$ for Songs by Male Artists



Notes: We plot the average value of $\log(\text{streams}_{it})$ for songs performed by male artists for each day from September 3, 2018, to December 23, 2018 with 95% confidence intervals.

Figure B.13. Event Study: $\log(\text{streams}_{it})$ - Songs by Female Artists and Matched Songs by Male Artists



Notes: In line with Equation 2.2, $\log(\text{streams}_{it})$ is regressed on song fixed effect and on the products between Female_i and a full set of dummy variables for each day from September 3, 2018, to December 23, 2019. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 8, 2018, is normalized to 0. The sample includes songs in the US Top 200 Spotify Charts. The songs by male artists in the control group have been restricted to match the Spotify song features by songs by female artists. We calculate a propensity score utilizing all Spotify song features and metadata. Subsequently, for each day, we pair each song by a female artist with a song by a male artist using a nearest neighbour approach. Standard Errors (5%) are clustered at song level.

Figure B.14. Share of Female, and Male Artists and Groups in the Spotify New Music Friday Playlist

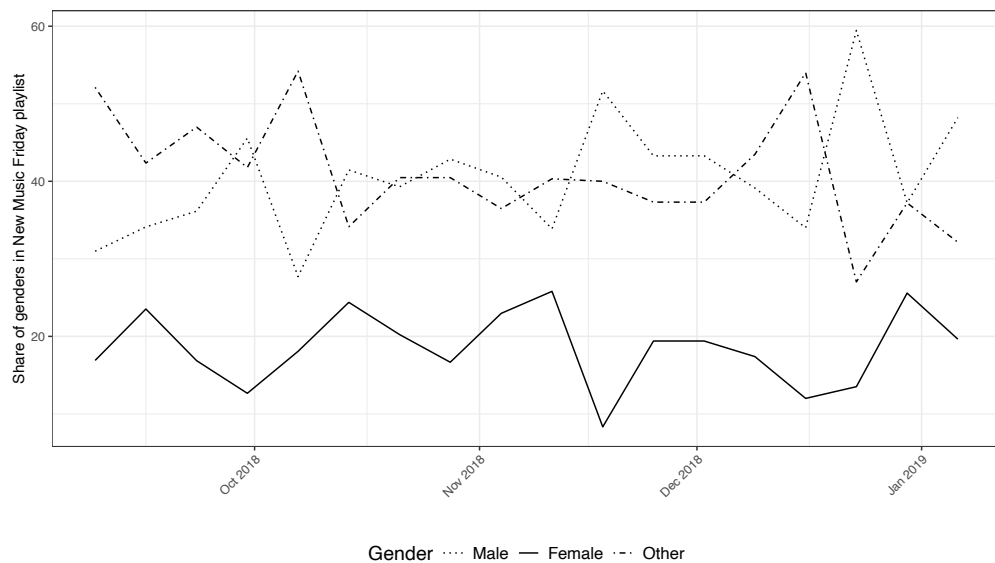


Table B.2. Difference-in-Differences: log(streams) - Songs by Female and Matched Songs by Male Artists: US.

Dependent Variable:	Log(Streams)			
Model:	(1)	(2)	(3)	(4)
$\text{Post}_i \times \text{Female}_i$	0.308** (0.128)	0.308*** (0.101)	0.121* (0.069)	0.101 (0.070)
<i>Fixed-effects</i>				
Artist	✓	✓		
Day	✓	✓	✓	✓
Song			✓	✓
Charts Controls	✓	✓	✓	✓
<i>Fit statistics</i>				
Observations	4,204	4,204	4,204	3,539
R ²	0.58564	0.63154	0.85773	0.85275
Within R ²	0.23317	0.31811	0.03510	0.02214

Notes: The sample includes songs within the top 200 US charts on Spotify from September 3, 2018, to December 23, 2019. The songs by male artists in the control group have been restricted to match the Spotify song features by songs by female artists. We calculate a propensity score using all Spotify song features and metadata. Then, for each day, we pair each song by a female artist with a song by a male artist using a nearest neighbour approach. Columns (1) and (2) use artist and day fixed effects, and in Column (2) we add song features controls. In Column (3), we incorporate song fixed effects. Columns (4) focus on songs from single artists. Standard errors are clustered by artist in Columns (1) and (2) and by song in Columns (3) and (4). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3. Difference-in-Differences: $\log(\text{streams}_{it})$ - Songs by Female Artists and Groups or Collaborations of More than Two Artists

Dependent Variable:	Log(Streams)			
Model:	(1)	(2)	(3)	(4)
$\text{Post}_t \times \text{Female}_i$	0.264 (0.203)	0.257*** (0.082)	0.168** (0.074)	0.048 (0.088)
<i>Fixed-effects</i>				
Artist	✓	✓		
Day	✓	✓	✓	✓
Song			✓	✓
<i>Fit statistics</i>				
Standard-Errors	Artist		Song	
Observations	7,069	7,069	7,069	3,668
R ²	0.52049	0.67220	0.85266	0.83294
Within R ²	0.02224	0.33159	0.01966	0.03776

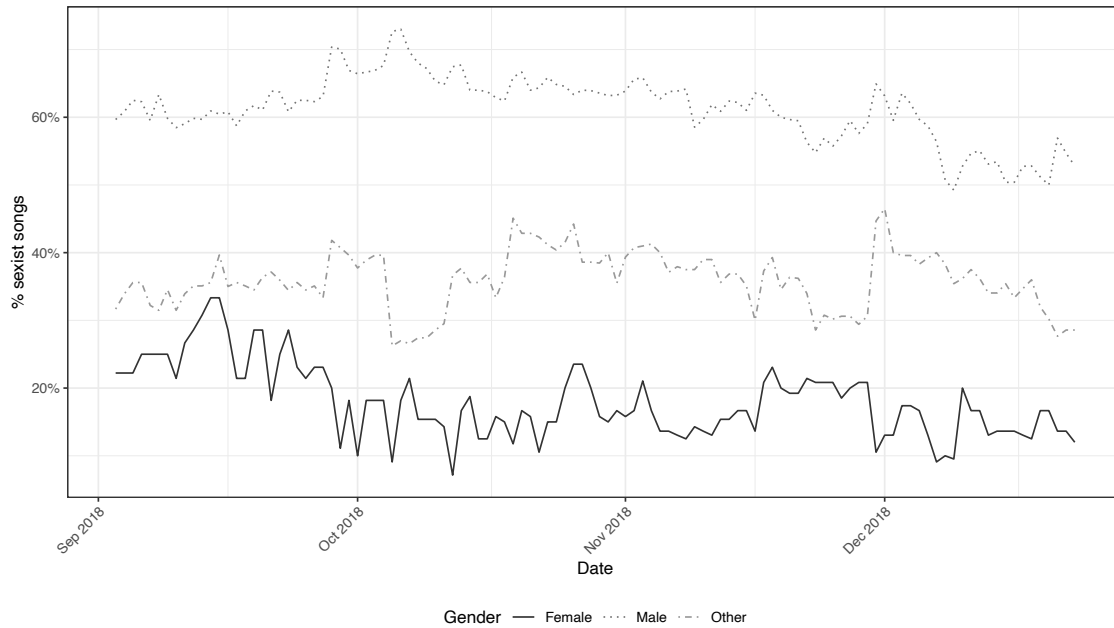
Notes: The sample includes songs within the top 200 US charts on Spotify from September 3, 2018, to December 23, 2018 by female artists and groups or collaborations of more than two artists. Columns (1) and (2) use artist and day fixed effects, and in Column (2) we add song features controls. In Column (3), we incorporate song fixed effects. Columns (4) focus on songs from single female artists. Standard errors are clustered by artist in Columns (1) and (2) and by song in Columns (3) and (4). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4. Difference-in-Differences: $\log(\text{streams}_{it})$ - Songs by Female and Male Artists without Top 5

Dependent Variable:	Log(Streams)			
Model:	(1)	(2)	(3)	(4)
$\text{Post}_t \times \text{Female}_i$	0.189* (0.099)	0.192** (0.089)	0.148** (0.070)	0.138** (0.070)
<i>Fixed-effects</i>				
Artist	✓	✓		
Day	✓	✓	✓	✓
Song			✓	✓
Charts Controls		✓		✓
<i>Fit statistics</i>				
Standard-Errors	Artist		Song	
Observations	15,749	15,749	15,749	15,749
R ²	0.37097	0.42969	0.78236	0.80456
Within R ²	0.00464	0.09755	0.00701	0.10833

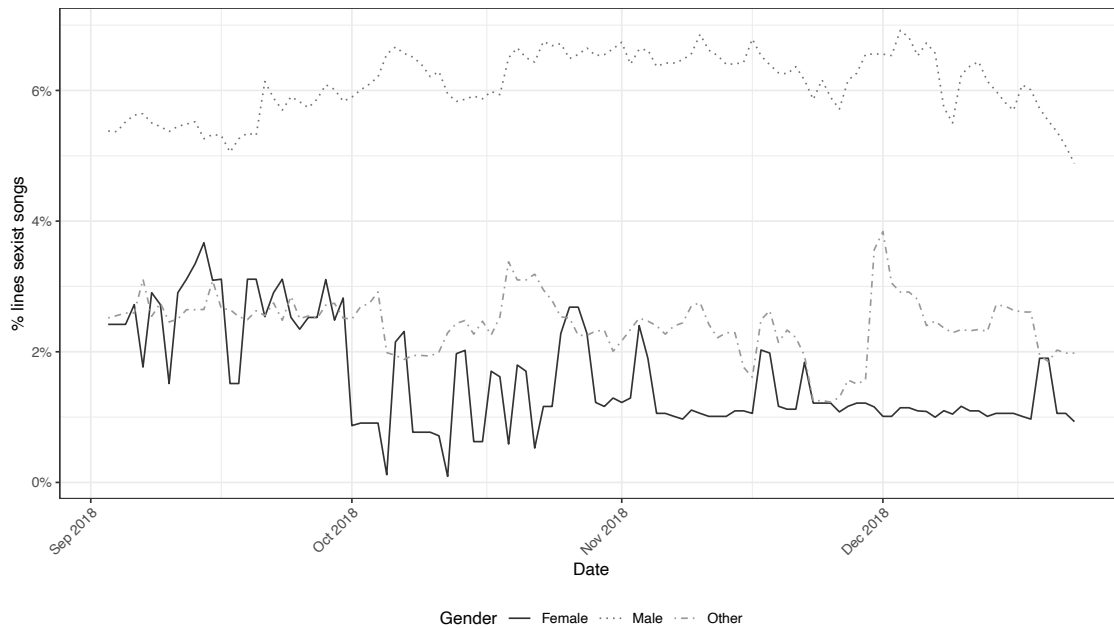
Notes: This table presents regression results analysing the impact of release timing and gender interactions on music streaming volumes. Columns (1) and (2) report results with standard errors clustered at the artist level, with Column (2) including release week dummies to account for initial release boosts and interactions between post-treatment periods and female artist identifiers, adjusted for artist fixed effects. Columns (3) and (4) use the same variables but adjust for song fixed effects, with standard errors clustered at the song level. Observations encompass 15,749 data points from the U.S. top 200 Spotify charts between September 3, 2018 and December 23, 2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure B.15. Daily Share of Songs with at least one Sexist Term



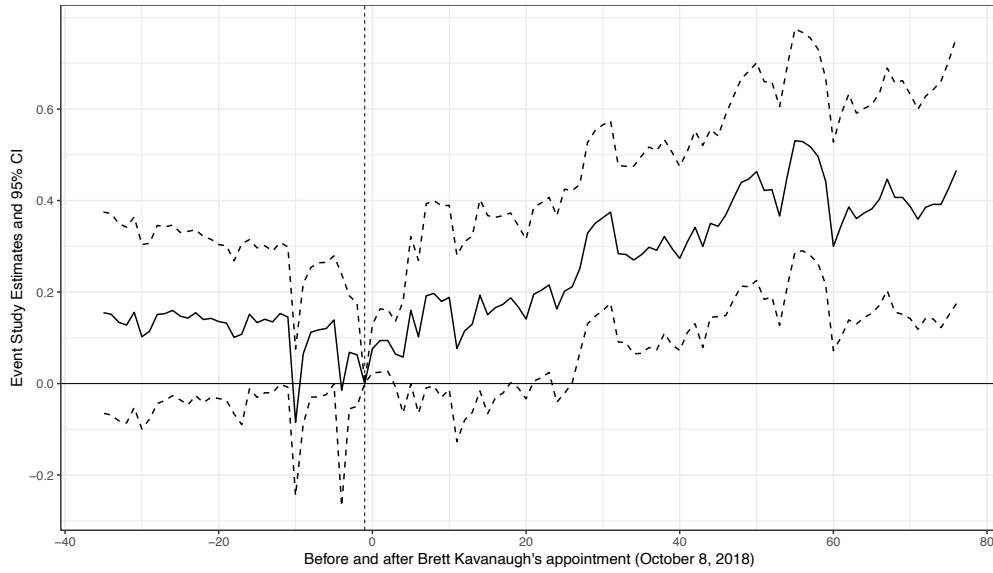
Notes: The figure presents the daily share of songs featuring at least one sexist term in their lyrics within the Spotify Top 200 US Spotify Charts for female and male artists and groups from September 3, 2018 to December 23, 2018.

Figure B.16. Daily Share of Lines with at least one Sexist Term



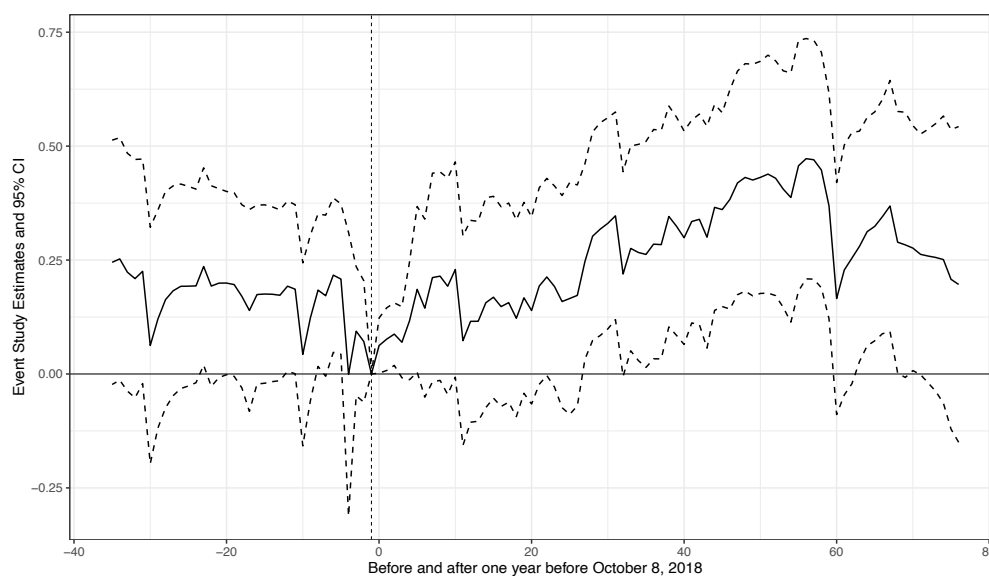
Notes: The figure illustrates the daily share of lines in songs' lyrics that contain at least one sexist term in the Spotify Top 200 US Spotify Charts. The analysis covers both female and male artists and groups from September 3, 2018 to December 23, 2018.

Figure B.17. Event Study: $\log(\text{streams}_{it})$ - Songs with Sexist Terms by Female and Male Artists



Notes: In line with Equation 2.2, $\log(\text{streams}_{it})$ is regressed on song fixed effect and on the products between Female_i and a full set of dummy variables for each day from September 3, 2018, to December 23, 2018. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 8, 2018, is normalized to 0. The sample includes songs in the US Top 200 Spotify Charts. We detect sexist terms in the songs' lyrics using the BERTweet model for sexism detection (Nguyen, Vu and Nguyen, 2020). We restrict the sample to songs with no sexist lines in their lyrics. Standard Errors (5%) are clustered at song level.

Figure B.18. Event Study: $\log(\text{streams}_{it})$ - Songs with no Sexist Terms by Female and Male Artists



Notes: In line with Equation 2.2, $\log(\text{streams}_{it})$ is regressed on song fixed effect and on the products between Female_i and a full set of dummy variables for each day from September 3, 2018, to December 23, 2018. The graphs plot the estimated coefficients on these products. The value of the coefficient corresponding to October 8, 2018, is normalized to 0. The sample includes songs in the US Top 200 Spotify Charts. We detect sexist terms in the songs' lyrics using the BERTweet model for sexism detection (Nguyen et al., 2020). We restrict the sample to songs with no sexist lines in their lyrics. Standard Errors (5%) are clustered at song level.

Table B.5. Difference-in-Differences: log (streams) - Songs by Female and Male Artists with at least one Sexist Line in the Lyrics.

Dependent Variable: Model:	Log(Streams)			
	(1)	(2)	(3)	(4)
$\text{Post}_t \times \text{Sexist}_t$	0.381*** (0.119)	-0.027 (0.048)	-0.033 (0.046)	-0.046 (0.046)
$\text{Post}_t \times \text{Sexist}_t \times \text{Female}_i$				0.491*** (0.123)
<i>Fixed-effects</i>				
Charts Controls	✓	✓	✓	✓
Song	✓	✓	✓	✓
Day	✓	✓	✓	✓
<i>Fit statistics</i>				
Standard-Errors		Song		
Observations	2,102	14,081	16,183	16,183
R ²	0.85303	0.83123	0.82730	0.82941
Within R ²	0.06072	0.16601	0.13859	0.14912

Notes: The sample includes songs within the top 200 US charts on Spotify from September 3, 2018, to December 23, 2018. We detect sexist terms in the songs' lyrics using the BERTweet model for sexism detection (Nguyen et al., 2020). We restrict the sample to songs with at least one sexist term in their lyrics. Column (1) models the effect of sexism on song streams for female artists, incorporating Song and Day fixed effects. Column (2) presents the same model but for male artists, controlling for Song and Day fixed effects. Column (3) analyses the effect of sexism on streams across all artists, using Song and Day fixed effects. Column (4) incorporates an interaction between sexism and gender (female) to capture gender-differentiated effects. In all models, standard errors are clustered by ISRC. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6. Difference-in-Differences: $\log(\text{streams}_{it})$ - Songs by Female and Male Artists with No Sexist Line in the Lyrics.

Dependent Variable: Model:	Log(Streams)			
	(1)	(2)	(3)	(4)
$\text{Post}_t \times \text{Female}_i$	0.295*** (0.088)	0.291*** (0.066)	0.176** (0.072)	0.157** (0.072)
<i>Fixed-effects</i>				
Artist	✓	✓		
Day	✓	✓	✓	✓
Song			✓	✓
Charts Controls		✓		✓
<i>Fit statistics</i>				
Standard-Errors	Artist		Song	
Observations	16,223	16,223	16,223	16,223
R ²	0.36002	0.44093	0.80071	0.82825
Within R ²	0.00857	0.13392	0.00828	0.14532

Notes: This table presents regression results analysing the impact of release timing and gender interactions on music streaming volumes. Columns (1) and (2) report results with standard errors clustered at the artist level, with Column (2) including release week dummies to account for initial release boosts and interactions between post-treatment periods and female artist identifiers, adjusted for artist fixed effects. Columns (3) and (4) use the same variables but adjust for song fixed effects, with standard errors clustered at the song level. Observations encompass 16,223 data points from the U.S. top 200 Spotify charts between September 3, 2018 and December 23, 2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.7. Difference-in-Differences: $\log(\text{streams})$ - Songs by Female and Male Artists considered empowering by LLAMA 3 model for different thresholds.

Dependent Variable: Model:	Log(Streams)		
	(1)	(2)	(3)
$\text{Post}_t \times \text{Female}_i$	0.087 (0.117)	0.107 (0.112)	0.111 (0.077)
$\text{Post}_t \times \text{Empowering}_i$	-0.207*** (0.022)	-0.207*** (0.022)	-0.207*** (0.022)
$\text{Post}_t \times \text{Female}_i \times \text{Empowering}_i$	0.285** (0.136)	0.286** (0.137)	0.311** (0.137)
<i>Fixed-effects</i>			
Song	✓	✓	✓
Day	✓	✓	✓
Empowerment Threshold	0.650	0.700	0.750
<i>Fit statistics</i>			
Observations	16,172	16,172	16,172
R ²	0.82853	0.82858	0.82865
Within R ²	0.14500	0.14527	0.14563

Notes: The sample includes songs within the top 200 charts on Spotify from September 3, 2018, to December 23, 2018. We detect empowering terms in the songs' lyrics using the LLAMA 3 model from Meta. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.8. Difference-in-Differences: log(streams) - Songs by Female and Male Artists considered empowering by LLAMA 3 model for: US.

Dependent Variable: Model:	Log(Streams)		
	(1)	(2)	(3)
$\text{Post}_t \times \text{Empowering}_i$	0.079 (0.138)	-0.222*** (0.021)	-0.207*** (0.022)
$\text{Post}_t \times \text{Female}_i$			0.111 (0.077)
$\text{Post}_t \times \text{Female}_i \times \text{Empowering}_i$			0.311** (0.137)
<i>Fixed-effects</i>			
Song	✓	✓	✓
Day	✓	✓	✓
Sample	Females	Males	All
Empowerment Threshold	0.750	0.750	0.750
Prompt Type	Examples	Examples	Examples
<i>Fit statistics</i>			
Observations	2,102	14,070	16,172
R ²	0.846	0.831	0.829
Within R ²	0.017	0.166	0.146

Notes: The sample includes songs within the top 200 US charts on Spotify from September 3, 2018, to December 23, 2018. We detect empowering terms in the songs' lyrics using the LLAMA 3 model from Meta. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table B.9

Dependent Variable: Model:	Log(Streams)		
	(1)	(2)	(3)
$\text{Post}_t \times \text{Female}_i$	0.268*** (0.100)	0.102 (0.066)	0.111 (0.077)
$\text{Post}_t \times \text{Empowering}_i$	0.045 (0.081)	-0.144 (0.129)	-0.207*** (0.022)
$\text{Post}_t \times \text{Female}_i \times \text{Empowering}_i$	-0.263* (0.140)	0.393** (0.195)	0.311** (0.137)
<i>Fixed-effects</i>			
Song	✓	✓	✓
Day	✓	✓	✓
Prompt Type	Blind	Sighted	Examples
Threshold	0.750	0.750	0.750
<i>Fit statistics</i>			
Observations	16,172	16,172	16,172
R ²	0.82919	0.82929	0.82865
Within R ²	0.14832	0.14882	0.14563

Notes: The sample includes songs within the top 200 US charts on Spotify from September 3, 2018, to December 23, 2018. We detect empowering terms in the songs' lyrics using the LLAMA 3 model from Meta. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.10. Difference-in-Differences: $\log(\text{streams})$ - Empowering songs by Label: US.

Dependent Variable: Model:	Log(Streams) (1)
$\text{Post}_t \times \text{Female}_i \times \text{Label} = \text{Universal}$	-0.427*** (0.115)
$\text{Post}_t \times \text{Female}_i \times \text{Label} = \text{Warner}$	-0.335** (0.138)
$\text{Post}_t \times \text{Female}_i$	0.476*** (0.107)
<i>Fixed-effects</i>	
Song	✓
Day	✓
<i>Fit statistics</i>	
Observations	16,223
R^2	0.83001
Within R^2	0.15410

Notes: The sample includes songs within the top 200 US charts on Spotify between September 03, 2018 and December 23, 2018. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Spotify Songs' Features

We provide here the full list of Spotify songs' features with their definition in line with the Spotify website:⁷

- **Acousticness:** A variable from 0.0 to 1.0 that indicates the likelihood of the track being acoustic.
- **Danceability:** This assesses how suitable a track is for dancing, based on tempo, rhythm stability, beat strength, and regularity. It ranges from 0.0 to 1.0.
- **Duration:** The length of the track in milliseconds.
- **Energy:** A value from 0.0 to 1.0 that represents the intensity and activity of a track, influenced by aspects like dynamic range, perceived loudness, and timbre.
- **Explicit:** Whether or not the track has explicit lyrics, 1 equals True, 0 equals False.
- **Instrumentalness:** Predicts the absence of vocals in a track, with values closer to 1.0 indicating higher likelihood of no vocal content.
- **Key:** The musical key of the track, using Pitch Class notation.
- **Liveness:** Indicates the probability of the track being recorded live.
- **Loudness:** The average loudness of the track in decibels (dB).
- **Mode:** Specifies the modality (major or minor) of a track.
- **Speechiness:** Assesses the presence of spoken words in a track.
- **Tempo:** The overall estimated tempo of a track in beats per minute (BPM).
- **Time Signature:** An estimated time signature indicating the number of beats in each bar.
- **Valence:** A measure describing the musical positiveness conveyed by a track, ranging from 0.0 to 1.0.

⁷For more information, see: <https://developer.spotify.com/documentation/web-api/reference/get-audio-features>.

C Chapter 3: Additional Tables and figures

Table C.1. Summary Statistics for continuous variables

Variable	Mean, Std. Dev.	25 th , 50 th , 75 th Percentiles	Min - Max	N
<i>Product Characteristics</i>				
Price (in NOK)	341.37, 452.47	100.00, 200.00, 400.00	1.00 - 4,999.00	3,048,284
Number of Likes	8.11, 16.08	2.00, 4.00, 9.00	0.00 - 1,658.00	3,048,284
Number of Images	2.79, 1.16	2.00, 3.00, 4.00	1.00 - 9.00	3,048,284
Product Title length	12.14, 4.47	9.00, 12.00, 16.00	2.00 - 49.00	3,048,284
Product Caption length	112.10, 107.18	44.00, 87.00, 148.00	0.00 - 3,223.00	3,048,284
<i>Profile Picture Variables¹</i>				
Age	29.41, 8.36	23.42, 28.19, 34.46	0.31 - 83.07	2,568,641
Number of Faces	1.04, 0.51	1.00, 1.00, 1.00	0.00 - 21.00	2,568,641
Number of People	1.19, 0.63	1.00, 1.00, 1.00	0.00 - 25.00	2,568,641
Percent of pixels occupied by the face	11.06, 11.28	2.94, 6.90, 16.32	0.05 - 99.60	2,358,685
Beauty	53.72, 15.16	42.25, 53.41, 64.88	9.06 - 96.19	2,568,641
Percentage of Head Keypoints present	77.15%, 19.56%	80.00%, 80.00%, 80.00%	0.00% - 100.00%	2,568,641
Percentage of Upper Body Keypoints present	45.94%, 34.86%	16.67%, 33.33%, 66.67%	0.00% - 100.00%	2,568,641
Percentage of Lower Body Keypoints present	15.57%, 29.14%	0.00%, 0.00%, 33.33%	0.00% - 100.00%	2,568,641
<i>Reputation Variables</i>				
Number of Reviews at Posting	13.89, 26.33	1.00, 5.00, 16.00	0.00 - 894.00	3,048,284
Average Rating at Posting	4.99, 0.12	5.00, 5.00, 5.00	1.00 - 5.00	2,445,812
Number of Reviews at Purchase	18.01, 30.43	2.00, 8.00, 21.00	0.00 - 1,014.00	3,048,284
Average Rating at Purchase	4.99, 0.11	5.00, 5.00, 5.00	1.00 - 5.00	2,714,364
Number of Products Posted	58.71, 85.62	12.00, 29.00, 68.00	1.00 - 973.00	3,048,284
Number of Products Sold	45.32, 73.29	7.00, 20.00, 52.00	0.00 - 953.00	3,048,284
<i>Additional Variables</i>				
Days to Sell	107.45, 168.42	2.06, 27.63, 144.61	0.00 - 1,181.60	3,048,284

¹Conditional on having a person in the profile picture. Price selected between 1 and 5000 Norwegian Kronas.

Figure C.1. Examples of product display



Informal setting without person



Catalogue Image setting without person



Informal setting with person



Catalogue Image with person

Figure C.2. User-Reported Gender Distribution of Accounts

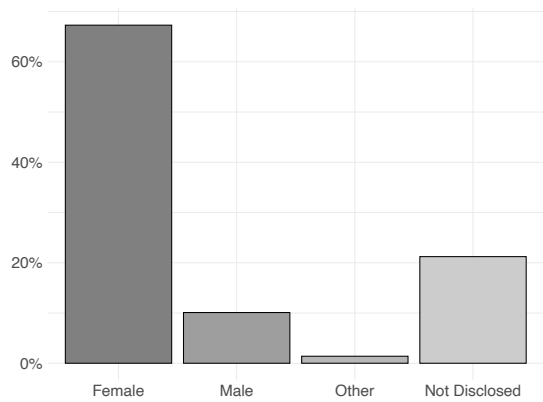


Figure C.3. User-Reported Gender Distribution of Products

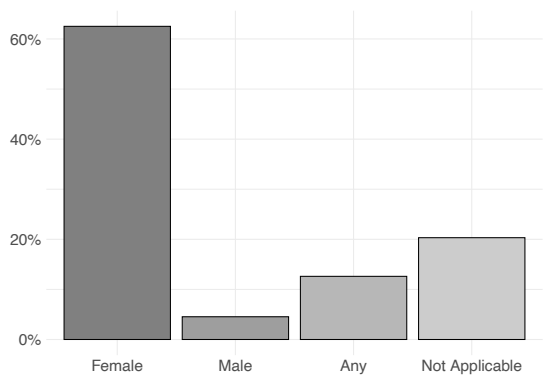


Figure C.4. User-Reported Gender Distribution of Products (Clothes Only)

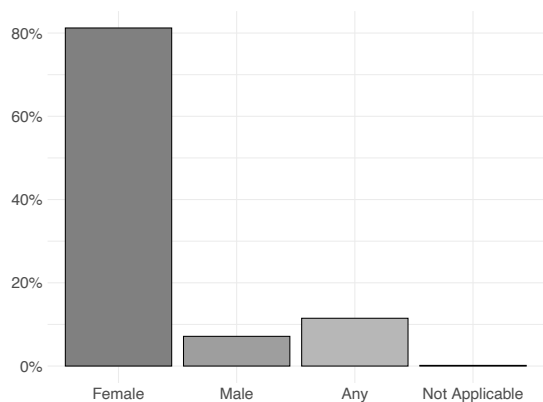


Figure C.5. Users across Norway

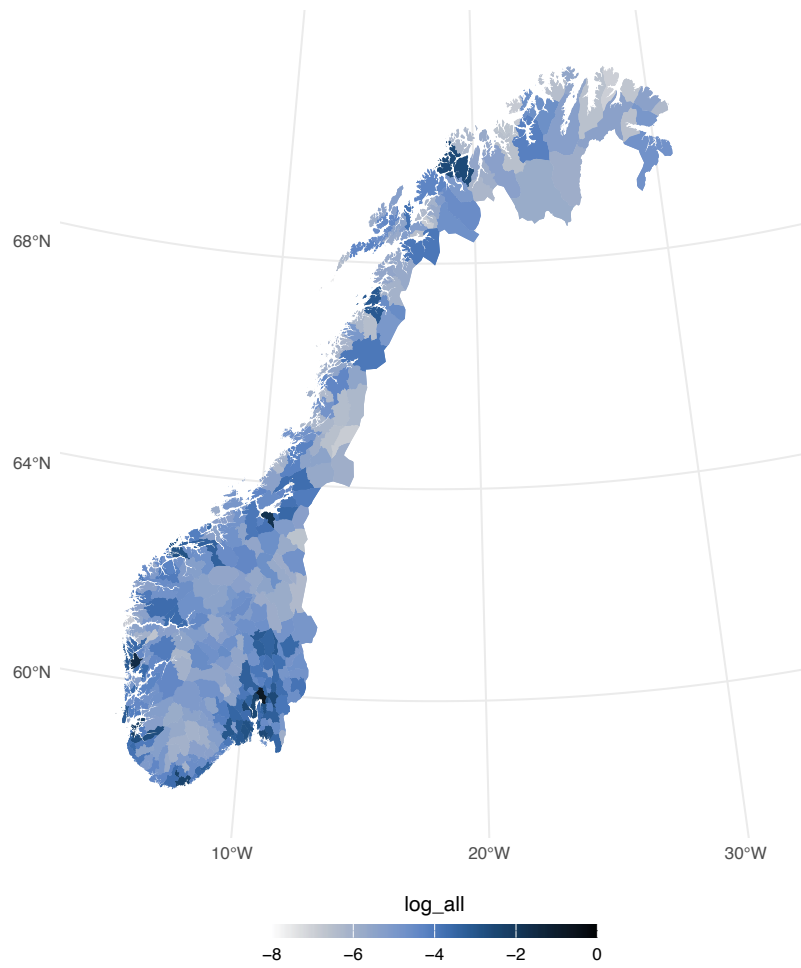


Figure C.6. Users in the Capital city, Oslo

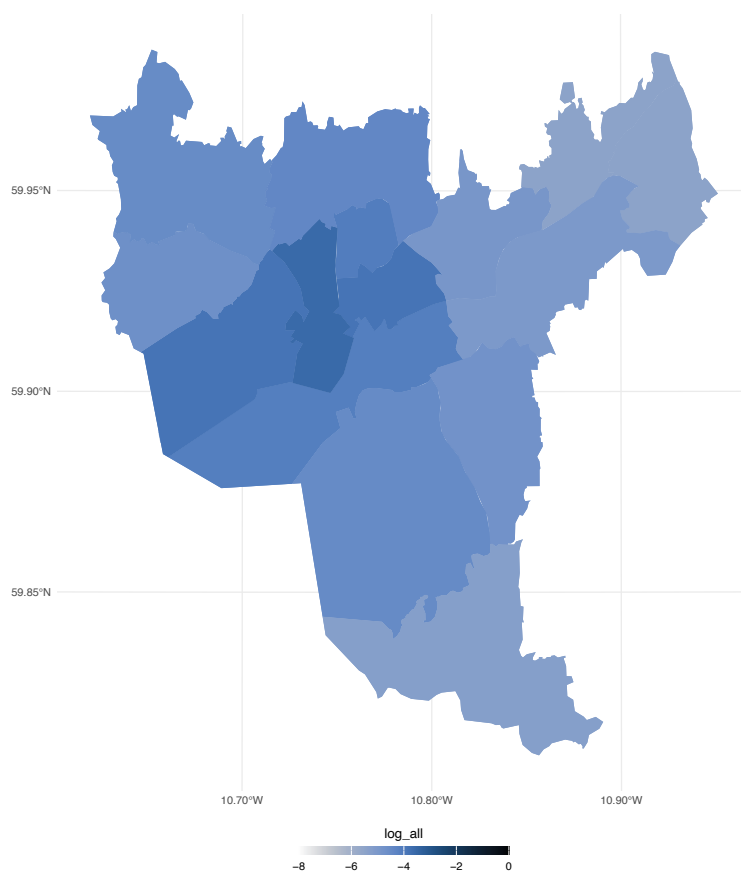


Figure C.7. Monthly User Registrations by Country

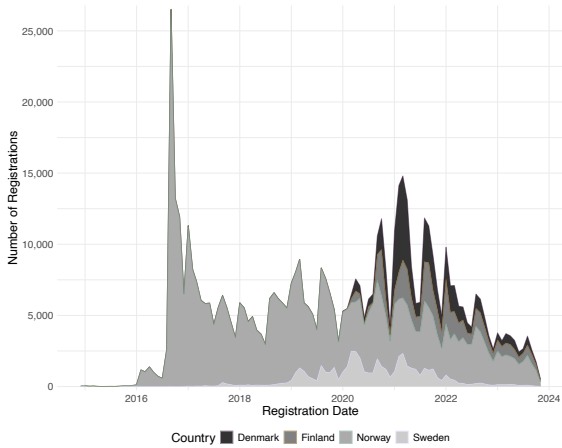


Figure C.8. Monthly User Registrations by Gender in Norway

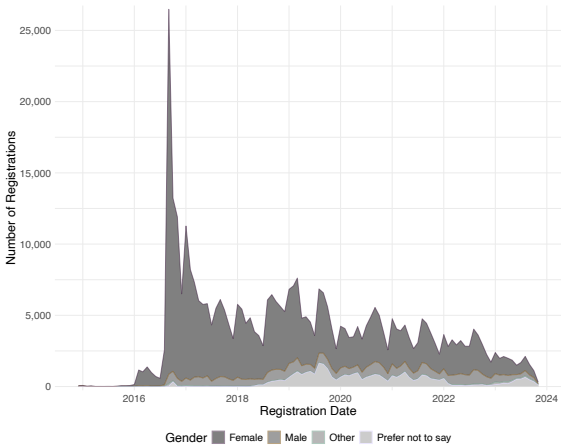


Figure C.9. Expansion of User Reviews Over Time

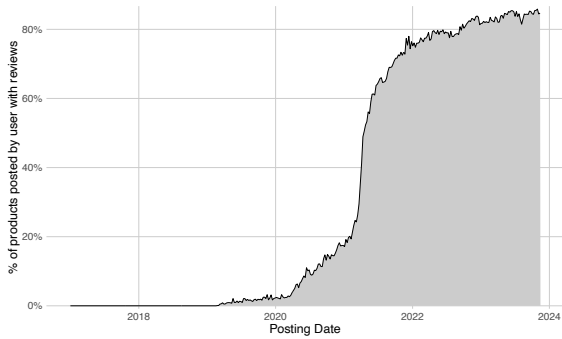


Figure C.10. Brand Disclosure Over Time

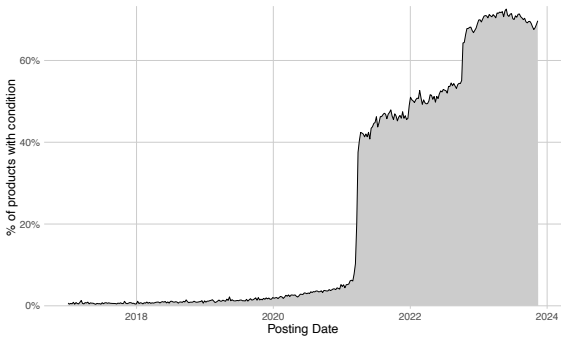


Figure C.11. Condition Disclosure Over Time

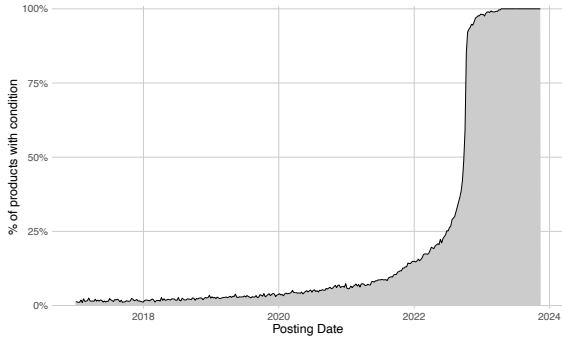


Figure C.12. Product Posting Percentage by Condition

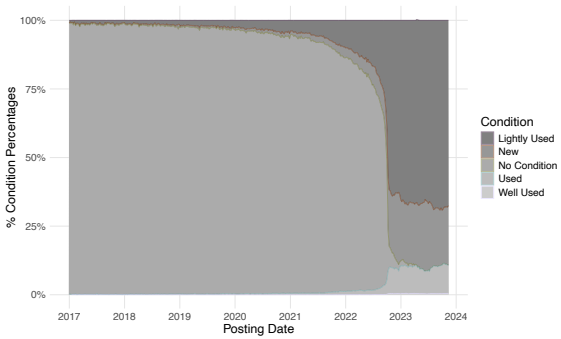




Figure C.13. Quintiles are calculated monthly per category, showing item distribution across quintiles 1 to 5.

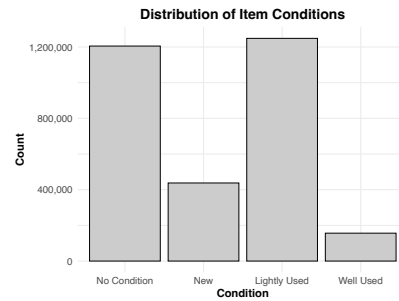


Figure C.14. Conditions include categories such as “No Condition,” “New,” “Lightly Used,” and “Well Used.”

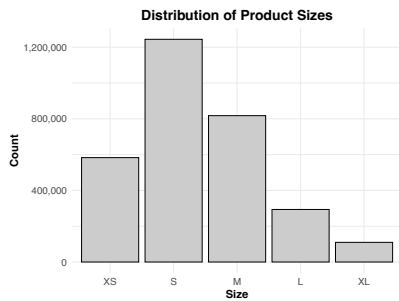


Figure C.15. Product Sizes are categorized as XS, S, M, L, and XL.

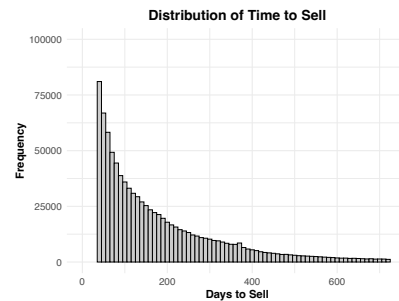


Figure C.16. Number of days it took to sell items, capped at 730 days (2 years).

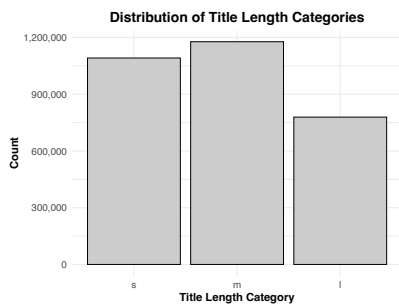


Figure C.17. Title lengths are divided into bins: “s” (0-10 characters), “m” (11-15 characters), and “l” (16+ characters).

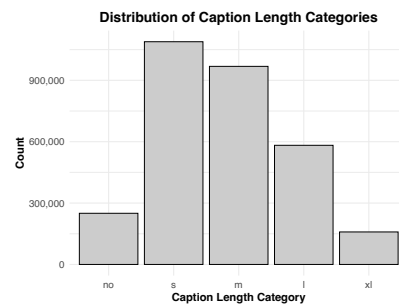


Figure C.18. Categories include: “no” (0 characters), “s” (1-75), “m” (76-150), “l” (151-300), and “xl” (301+).

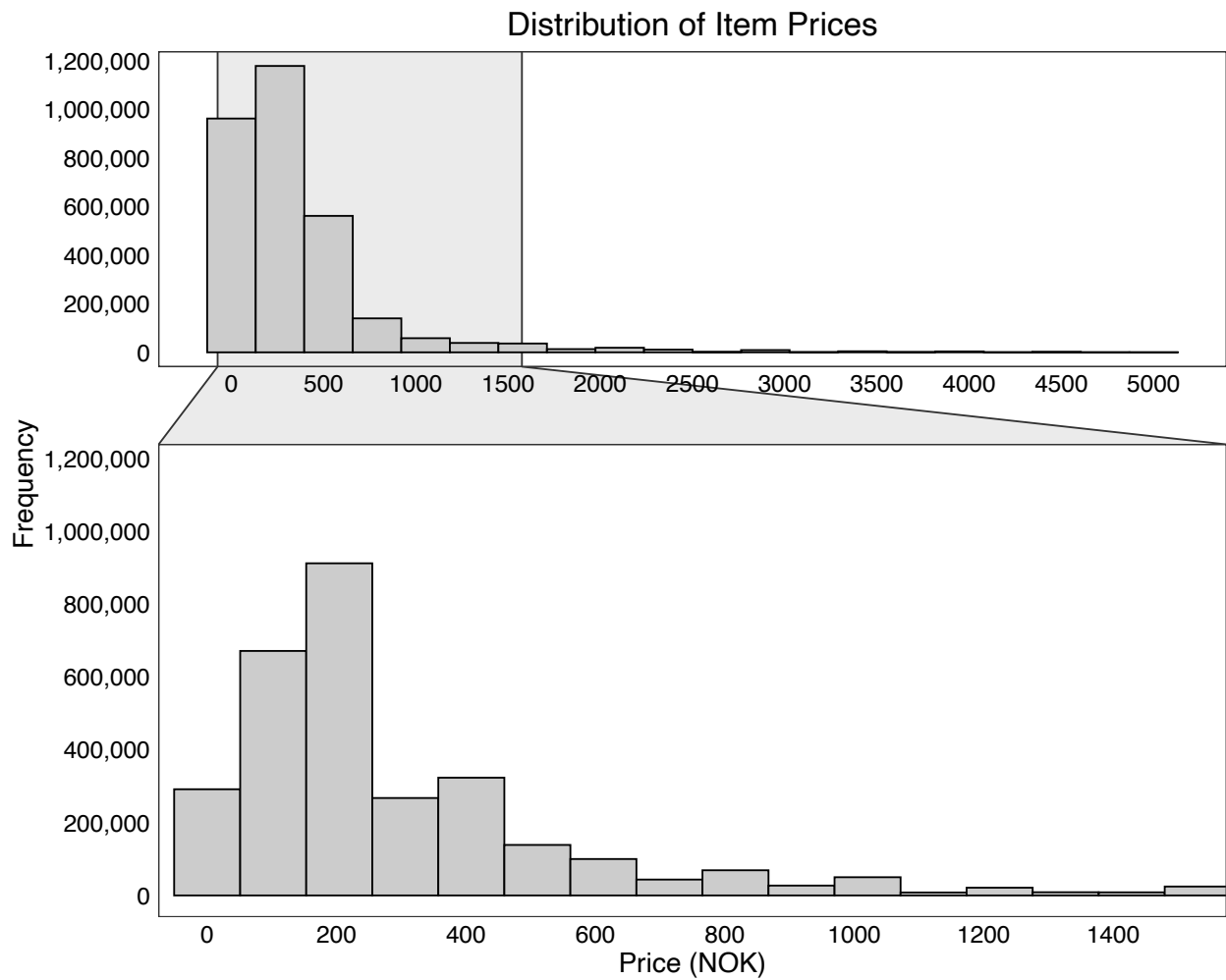
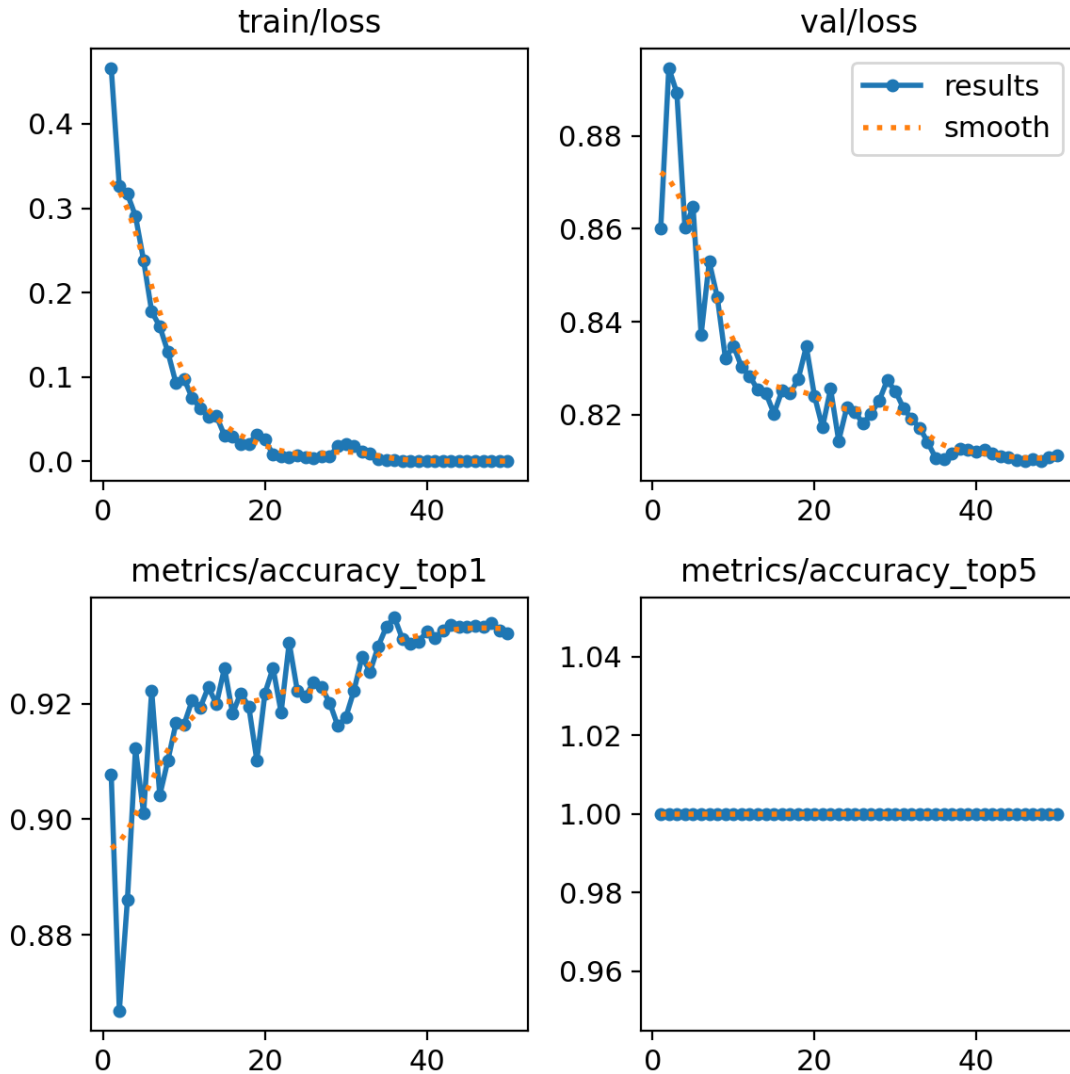


Figure C.19. The histogram shows the distribution of item prices rounded to the nearest NOK 10.

Figure C.20. Training Performance of an Image Classification Model



Notes: This figure presents the training results of an image classification model across different categories. The top-left and top-right plots display the training loss and validation loss, both decreasing over time, indicating model convergence. The bottom-left plot shows the Top-1 accuracy, which improves throughout training, stabilizing above 92%. Since there are only four categories to predict, the Top-5 accuracy (bottom-right) remains at 100%. The dotted orange line represents a smoothed trend for better visualization. These results indicate effective learning, though fluctuations in validation loss may suggest some degree of overfitting or variability.

Beauty

Figure C.21. Distribution of beauty per product

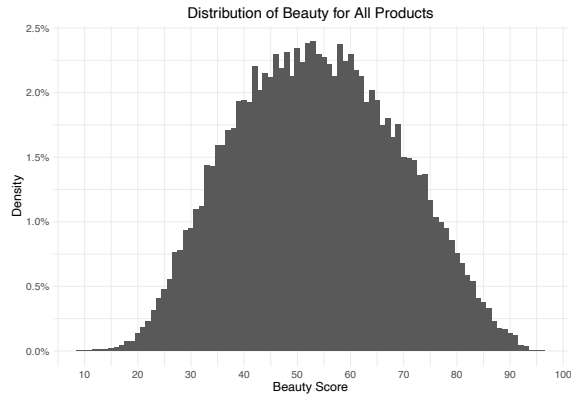


Figure C.22. Distribution of beauty per user

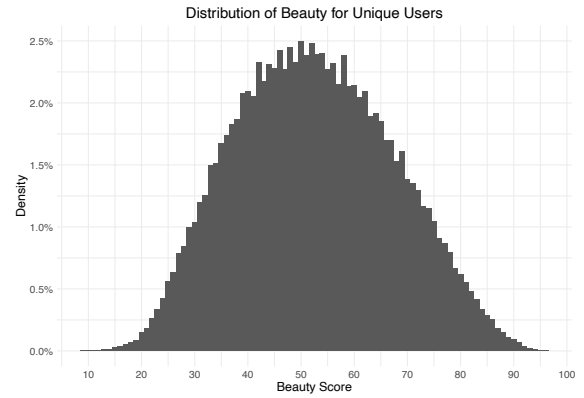


Figure C.23. QQ Plot of Beauty Score for All Products

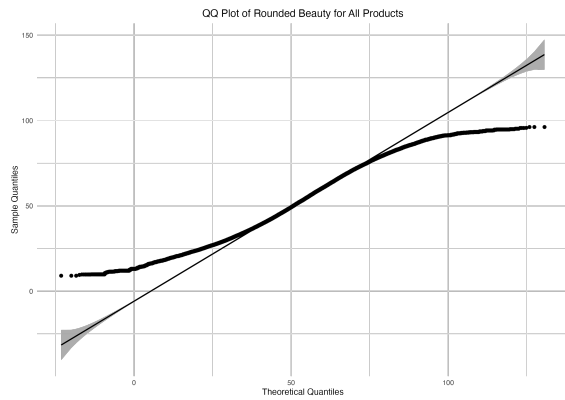


Figure C.24. QQ Plot of Beauty Score for Unique Users

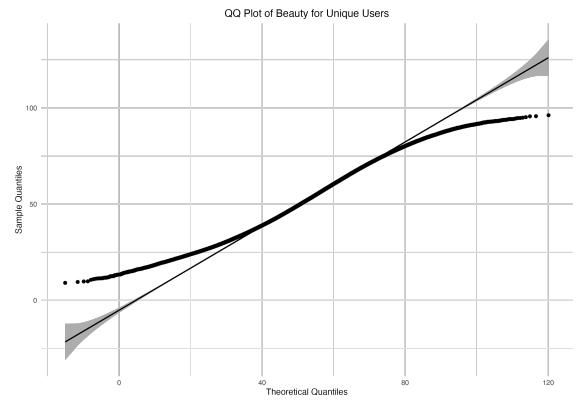


Figure C.25. Average number of items posted per Beauty Category

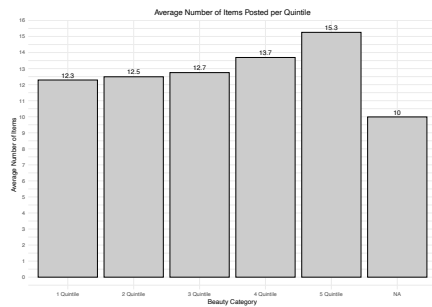


Figure C.26. Percentage of items sold per Beauty Category

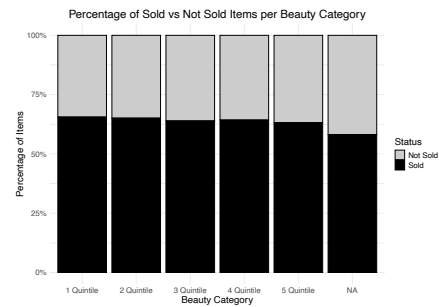


Table C.2. Logistic Regression Sold (0/1)

Dependent Variable: Category Model:	Sold Outcome (0/1)					
	Full sample (1)	Sweaters (2)	Tops (3)	Pants (4)	Dresses (5)	Jackets (6)
Real Person	0.036 (0.108)	-0.122*** (0.012)	-0.027* (0.016)	-0.136*** (0.013)	0.339*** (0.010)	0.010 (0.013)
Professional Model	0.235* (0.138)	0.079*** (0.016)	0.083*** (0.019)	0.006 (0.013)	0.577*** (0.011)	0.182*** (0.017)
Catalogue Image	0.212*** (0.069)	0.143*** (0.018)	0.357*** (0.025)	-0.032 (0.020)	0.333*** (0.018)	0.242*** (0.018)
Price Quintile: 2	0.062*** (0.019)	0.094*** (0.015)	0.012 (0.018)	0.026* (0.014)	0.050*** (0.012)	0.110*** (0.015)
Price Quintile: 3	0.210*** (0.022)	0.263*** (0.014)	0.126*** (0.021)	0.186*** (0.016)	0.180*** (0.013)	0.221*** (0.016)
Price Quintile: 4	0.353*** (0.035)	0.435*** (0.015)	0.273*** (0.023)	0.325*** (0.016)	0.282*** (0.013)	0.383*** (0.017)
Price Quintile: 5	0.514*** (0.053)	0.622*** (0.016)	0.637*** (0.022)	0.379*** (0.017)	0.426*** (0.014)	0.497*** (0.019)
Condition Disclosed	-0.175** (0.077)	-0.100 (0.097)	0.156 (0.160)	-0.306*** (0.118)	-0.113 (0.103)	-0.441*** (0.129)
Beauty	-0.0009*** (0.0003)	-0.0010*** (0.0004)	-0.0007 (0.0005)	-0.0007* (0.0004)	-0.0009*** (0.0003)	-0.002*** (0.0004)
Person in Profile Picture	0.114*** (0.009)	0.123*** (0.023)	0.096*** (0.030)	0.109*** (0.022)	0.114*** (0.018)	0.152*** (0.024)
Number of Images	0.047*** (0.006)	0.064*** (0.005)	0.047*** (0.006)	0.051*** (0.005)	0.034*** (0.004)	0.052*** (0.005)
Log(1 + Reviews at Purchase)	0.393*** (0.021)	0.448*** (0.004)	0.422*** (0.006)	0.413*** (0.004)	0.352*** (0.003)	0.361*** (0.005)
Log(1 + (Posted - Sold))	-0.582*** (0.016)	-0.630*** (0.004)	-0.581*** (0.005)	-0.601*** (0.004)	-0.553*** (0.003)	-0.555*** (0.004)
Log(1 + Number of Likes)	0.151*** (0.022)	0.141*** (0.005)	0.184*** (0.007)	0.150*** (0.005)	0.076*** (0.004)	0.182*** (0.006)
Brand	✓	✓	✓	✓	✓	✓
Caption	✓	✓	✓	✓	✓	✓
Color	✓	✓	✓	✓	✓	✓
Material	✓	✓	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓	✓	✓
Size	✓	✓	✓	✓	✓	✓
Years	2023	2023	2023	2023	2023	2023
<i>Fixed-effects</i>						
Category	✓	✓	✓	✓	✓	✓
<i>Fit statistics</i>						
Standard-Errors	Category			IID		
Observations	1,108,423	228,631	132,243	223,198	333,749	190,602
Squared Correlation	0.190	0.215	0.192	0.185	0.183	0.177
Pseudo R ²	0.149	0.170	0.151	0.146	0.142	0.139
BIC	1,308,891.1	263,326.5	152,575.7	264,506.7	396,943.9	227,217.0

Notes: This table presents regression results analysing sales using a logit model over the whole sample and 5 categories with a total of 1,108,423 observations. The table differentiates from others by using "Price quintile" as a categorical variable with the first quintile (lowest prices) as the reference. Quintiles are calculated on a category and monthly basis. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table C.3. Logist Regression Sold (0/1) - Beauty Picture Interaction - 2023

Dependent Variable: Category Model:	Sold Outcome (0/1)					
	Full sample (1)	Sweaters (2)	Tops (3)	Pants (4)	Dresses (5)	Jackets (6)
Real Person	-0.021 (0.110)	-0.189*** (0.025)	-0.037 (0.034)	-0.170*** (0.025)	0.277*** (0.021)	-0.078*** (0.027)
Catalogue Image	0.150 (0.099)	0.070** (0.034)	0.403*** (0.048)	-0.157*** (0.037)	0.348*** (0.036)	0.126*** (0.035)
Professional Model	0.197 (0.141)	-0.002 (0.033)	0.107*** (0.040)	2.32×10^{-5} (0.024)	0.546*** (0.021)	0.092*** (0.034)
Beauty Category $\times$ Real Person	0.001*** (0.0003)	0.002*** (0.0005)	0.0002 (0.0006)	0.0007 (0.0005)	0.001*** (0.0004)	0.002*** (0.0005)
Beauty Category $\times$ Catalogue Image	0.001* (0.0007)	0.001** (0.0007)	-0.001 (0.0009)	0.003*** (0.0007)	-0.0004 (0.0007)	0.002*** (0.0007)
Beauty Category $\times$ Professional Model	0.0009** (0.0004)	0.002*** (0.0006)	-0.0004 (0.0007)	3.42×10^{-5} (0.0005)	0.0008* (0.0004)	0.002*** (0.0007)
Beauty Category	-0.002*** (0.0004)	-0.002*** (0.0004)	-0.0004 (0.0005)	-0.001** (0.0004)	-0.001*** (0.0004)	-0.003*** (0.0004)
Person in Profile Picture	0.122*** (0.011)	0.137*** (0.022)	0.086*** (0.030)	0.114*** (0.022)	0.123*** (0.018)	0.167*** (0.024)
Brand	✓	✓	✓	✓	✓	✓
Condition	✓	✓	✓	✓	✓	✓
Caption	✓	✓	✓	✓	✓	✓
Color	✓	✓	✓	✓	✓	✓
Material	✓	✓	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓	✓	✓
Price	✓	✓	✓	✓	✓	✓
Reviews	✓	✓	✓	✓	✓	✓
Size	✓	✓	✓	✓	✓	✓
<i>Fixed-effects</i>						
Category	✓	✓	✓	✓	✓	✓
<i>Fit statistics</i>						
Years	2023	2023	2023	2023	2023	2023
Standard-Errors	Category			IID		
Observations	1,108,423	228,631	132,243	223,198	333,749	190,602
Squared Correlation	0.190	0.214	0.192	0.185	0.183	0.176
Pseudo R ²	0.149	0.170	0.150	0.146	0.142	0.139
BIC	1,309,370.1	263,513.3	152,654.3	264,634.9	397,035.1	227,323.3

Notes: This table presents logistic regression results analysing the relationship between image categories and the likelihood of a product being sold across the full sample and five subcategories (Sweaters, Tops, Pants, Dresses, and Jackets), using a total of 1,108,423 observations. Interaction terms with the Beauty Category variable (constructed by dividing the beauty score into deciles) capture how the attractiveness of images influences sales likelihood differently for each image type. Fixed effects are applied at the category level, and controls include brand, product condition, caption length, colour, material, month of posting, price, reviews, and size. Standard errors are clustered by category. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table C.4. Logistic Regression on Picture Type choice for Sweaters

Dependent Variables: Category Model:	Homemade Image (1)	Real Person (2)	Catalogue Image Sweaters (3)	Professional Model (4)
Price Quintile: Linear	-0.683*** (0.012)	-0.013 (0.013)	0.819*** (0.021)	0.867*** (0.018)
Condition Disclosed	0.087 (0.107)	0.017 (0.117)	-0.175 (0.163)	-0.069 (0.149)
Log(1 + Reviews at Posting)	-0.199*** (0.006)	0.099*** (0.006)	0.144*** (0.010)	0.173*** (0.009)
Log(1 + (Posted - Sold))	-0.009* (0.005)	0.104*** (0.006)	-0.071*** (0.009)	-0.101*** (0.007)
Log(Posted)	0.120*** (0.007)	-0.119*** (0.007)	-0.122*** (0.011)	0.013 (0.010)
Beauty	-0.019*** (0.0003)	0.017*** (0.0004)	0.003*** (0.0006)	0.009*** (0.0005)
Number of Images	-0.068*** (0.005)	0.115*** (0.006)	-0.253*** (0.009)	0.127*** (0.007)
Brand	✓	✓	✓	✓
Caption	✓	✓	✓	✓
Color	✓	✓	✓	✓
Material	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓
Size	✓	✓	✓	✓
Year	2023	2023	2023	2023
<i>Fixed-effects</i>				
Category	✓	✓	✓	✓
<i>Fit statistics</i>				
Standard-Errors			IID	
Observations	182,542	182,542	182,542	182,542
Squared Correlation	0.112	0.058	0.042	0.049
Pseudo R ²	0.085	0.052	0.064	0.067
BIC	230,571.0	194,097.3	98,324.9	124,266.7

Notes: This table presents logistic regression results analysing the determinants of image type choice in product listings on a second-hand marketplace. The dependent variables represent different image categories: Homemade Image, Real Person, Catalogue Image, and Professional Model. The regression analyses in detail the Sweaters. Controls for brand, caption length, colour, material, month of posting, and size are included. Fixed effects are applied at the category level. Standard errors are clustered by category. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table C.5. Logistic Regression on Picture Type choice for Tops

Dependent Variables: Category Model:	Homemade Image	Real Person	Catalogue Image Tops	Professional Model
	(1)	(2)	(3)	(4)
Price Quintile: Linear	-0.905*** (0.016)	0.346*** (0.017)	0.438*** (0.029)	0.857*** (0.022)
Condition Disclosed	0.200 (0.181)	-0.183 (0.176)	0.532 (0.390)	-0.251 (0.208)
Log(1 + Reviews at Posting)	-0.216*** (0.007)	0.130*** (0.008)	0.147*** (0.013)	0.110*** (0.010)
Log(1 + (Posted - Sold))	0.032*** (0.007)	0.062*** (0.007)	-0.113*** (0.012)	-0.088*** (0.008)
Log(Posted)	0.086*** (0.009)	-0.046*** (0.009)	-0.165*** (0.015)	-0.001 (0.011)
Beauty	-0.019*** (0.0004)	0.014*** (0.0005)	0.002** (0.0008)	0.011*** (0.0006)
Number of Images	-0.077*** (0.007)	0.060*** (0.007)	-0.219*** (0.012)	0.149*** (0.009)
Brand	✓	✓	✓	✓
Caption	✓	✓	✓	✓
Color	✓	✓	✓	✓
Material	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓
Size	✓	✓	✓	✓
Year	2023	2023	2023	2023
<i>Fixed-effects</i>				
Category	✓	✓	✓	✓
<i>Fit statistics</i>				
Standard-Errors			IID	
Observations	108,137	108,137	108,137	108,137
Squared Correlation	0.134	0.072	0.023	0.051
Pseudo R ²	0.102	0.062	0.037	0.058
BIC	135,451.7	123,218.3	53,957.5	88,427.5

Notes: This table presents logistic regression results analysing the determinants of image type choice in product listings on a second-hand marketplace. The dependent variables represent different image categories: Homemade Image, Real Person, Catalogue Image, and Professional Model. The regression analyses in detail the Tops. Controls for brand, caption length, colour, material, month of posting, and size are included. Fixed effects are applied at the category level. Standard errors are clustered by category. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table C.6. Logistic Regression on Picture Type choice for Pants

Dependent Variables: Category Model:	Homemade Image (1)	Real Person (2)	Catalogue Image Pants (3)	Professional Model (4)
Price Quintile: Linear	-0.641*** (0.013)	-0.050*** (0.014)	0.528*** (0.025)	0.709*** (0.015)
Condition Disclosed	0.269** (0.128)	-0.051 (0.132)	0.134 (0.240)	-0.285** (0.128)
Log(1 + Reviews at Posting)	-0.226*** (0.006)	0.123*** (0.006)	0.083*** (0.011)	0.144*** (0.007)
Log(1 + (Posted - Sold))	0.024*** (0.005)	0.089*** (0.006)	-0.032** (0.010)	-0.107*** (0.006)
Log(Posted)	0.111*** (0.007)	-0.094*** (0.008)	-0.090*** (0.013)	-0.023** (0.007)
Beauty	-0.020*** (0.0003)	0.016*** (0.0004)	0.0004 (0.0007)	0.009*** (0.0004)
Number of Images	0.083*** (0.005)	0.049*** (0.006)	-0.260*** (0.010)	-0.063*** (0.006)
Brand	✓	✓	✓	✓
Caption	✓	✓	✓	✓
Color	✓	✓	✓	✓
Material	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓
Size	✓	✓	✓	✓
Year	2023	2023	2023	2023
<i>Fixed-effects</i>				
Category	✓	✓	✓	✓
<i>Fit statistics</i>				
Standard-Errors			IID	
Observations	174,589	174,589	174,589	174,589
Squared Correlation	0.119	0.059	0.019	0.055
Pseudo R ²	0.090	0.054	0.036	0.052
BIC	219,283.2	184,771.7	79,952.5	185,226.4

Notes: This table presents logistic regression results analysing the determinants of image type choice in product listings on a second-hand marketplace. The dependent variables represent different image categories: Homemade Image, Real Person, Catalogue Image, and Professional Model. The regression analyses in detail the Pants. Controls for brand, caption length, colour, material, month of posting, and size are included. Fixed effects are applied at the category level. Standard errors are clustered by category. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table C.7. Logistic Regression on Picture Type choice for Dresses

Dependent Variables: Category Model:	Homemade Image	Real Person	Catalogue Image Dresses	Professional Model
	(1)	(2)	(3)	(4)
Price Quintile: Linear	-1.36*** (0.011)	0.404*** (0.011)	0.601*** (0.022)	1.12*** (0.012)
Condition Disclosed	0.146 (0.120)	-0.112 (0.119)	-0.107 (0.223)	0.006 (0.124)
Log(1 + Reviews at Posting)	-0.170*** (0.005)	0.063*** (0.005)	0.058*** (0.010)	0.139*** (0.005)
Log(1 + (Posted - Sold))	0.121*** (0.004)	0.025*** (0.005)	-0.080*** (0.009)	-0.144*** (0.005)
Log(Posted)	-0.030*** (0.006)	0.009 (0.006)	-0.006 (0.011)	0.017** (0.006)
Beauty	-0.025*** (0.0003)	0.016*** (0.0003)	0.002** (0.0006)	0.013*** (0.0003)
Number of Images	-0.010** (0.004)	0.004 (0.004)	-0.170*** (0.009)	0.059*** (0.005)
Brand	✓	✓	✓	✓
Caption	✓	✓	✓	✓
Color	✓	✓	✓	✓
Material	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓
Size	✓	✓	✓	✓
Year	2023	2023	2023	2023
<i>Fixed-effects</i>				
Category	✓	✓	✓	✓
<i>Fit statistics</i>				
Standard-Errors			IID	
Observations	272,095	272,095	272,095	272,095
Squared Correlation	0.185	0.059	0.014	0.090
Pseudo R ²	0.144	0.051	0.031	0.086
BIC	321,994.9	294,494.3	109,443.4	273,224.4

Notes: This table presents logistic regression results analysing the determinants of image type choice in product listings on a second-hand marketplace. The dependent variables represent different image categories: Homemade Image, Real Person, Catalogue Image, and Professional Model. The regression analyses in detail the Dresses. Controls for brand, caption length, colour, material, month of posting, and size are included. Fixed effects are applied at the category level. Standard errors are clustered by category. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table C.8. Logistic Regression on Picture Type choice for Jackets

Dependent Variables: Category Model:	Homemade Image	Real Person	Catalogue Image Jackets	Professional Model
	(1)	(2)	(3)	(4)
Price Quintile: Linear	-1.23*** (0.014)	0.211*** (0.016)	1.20*** (0.024)	1.26*** (0.022)
Condition Disclosed	0.092 (0.138)	0.118 (0.153)	-0.045 (0.203)	-0.323* (0.169)
Log(1 + Reviews at Posting)	-0.197*** (0.006)	0.093*** (0.007)	0.105*** (0.010)	0.175*** (0.009)
Log(1 + (Posted - Sold))	0.013** (0.006)	0.073*** (0.006)	-0.073*** (0.009)	-0.080*** (0.008)
Log(Posted)	0.052*** (0.007)	-0.052*** (0.008)	-0.050*** (0.011)	0.016 (0.010)
Beauty	-0.018*** (0.0004)	0.015*** (0.0004)	0.004*** (0.0006)	0.009*** (0.0005)
Number of Images	9.85×10^{-5} (0.005)	0.149*** (0.006)	-0.274*** (0.009)	-0.015** (0.008)
Brand	✓	✓	✓	✓
Caption	✓	✓	✓	✓
Colour	✓	✓	✓	✓
Material	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓
Size	✓	✓	✓	✓
Year	2023	2023	2023	2023
<i>Fixed-effects</i>				
Category	✓	✓	✓	✓
<i>Fit statistics</i>				
Standard-Errors			IID	
Observations	151,265	151,265	151,265	151,265
Squared Correlation	0.152	0.042	0.059	0.063
Pseudo R ²	0.116	0.039	0.080	0.085
BIC	185,444.2	157,414.0	93,208.9	106,955.3

Notes: This table presents logistic regression results analysing the determinants of image type choice in product listings on a second-hand marketplace. The dependent variables represent different image categories: Homemade Image, Real Person, Catalogue Image, and Professional Model. The regression analyses in detail the Jackets. Controls for brand, caption length, colour, material, month of posting, and size are included. Fixed effects are applied at the category level. Standard errors are clustered by category. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table C.9. Logist Regresssion Sold (0/1) - Beauty Picture Interaction Category

Dependent Variable: Model:	Sold Outcome (0/1)			
	(1)	(2)	(3)	(4)
Real Person	0.154* (0.081)	-0.301* (0.176)	-0.008 (0.118)	0.048 (0.104)
Catalogue Image	0.354*** (0.076)	0.056 (0.111)	0.195*** (0.064)	0.172* (0.103)
Professional Model	0.240 (0.160)	0.194 (0.134)	0.243* (0.141)	0.205 (0.141)
Distance from Average Beauty $\times$ Real Person	0.009** (0.004)	0.011** (0.004)	0.004*** (0.001)	
Distance from Average Beauty $\times$ Catalogue Image	0.010*** (0.003)	0.006* (0.003)	0.002 (0.001)	
Distance from Average Beauty $\times$ Professional Model	-0.001 (0.004)	0.0006 (0.006)	0.0010 (0.0008)	
Distance from Average Beauty	-0.005*** (0.002)	-0.002 (0.003)	-0.003*** (0.0006)	
Brand	✓	✓	✓	✓
Condition	✓	✓	✓	✓
Caption	✓	✓	✓	✓
Color	✓	✓	✓	✓
Material	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓
Price	✓	✓	✓	✓
Reviews	✓	✓	✓	✓
Size	✓	✓	✓	✓
Beauty Sample Year	Bottom 2023	Top 2023	The middle 2023	No Profile Picture 2023
<i>Fixed-effects</i> Category	✓	✓	✓	✓
<i>Fit statistics</i>				
Standard-Errors			Category	
Observations	100,000	100,000	702,594	205,829
Squared Correlation	0.195	0.175	0.188	0.197
Pseudo R ²	0.155	0.136	0.147	0.154
BIC	117,785.3	120,780.8	831,348.5	241,318.4

Notes: This table presents regression results analysing sales using a logit model over the whole sample and 5 categories with a total of 702,594 observations. * p < 0.10, ** p < 0.05, *** p < 0.01.

Variables Description

- Sale Outcome $_{i,j}$ is a binary variable indicating whether the product i was sold (1) or remained unsold (0).
- Picture Category $_i$: A set of variables indicating the category of the image, distinguishing whether the first picture of the product is a homemade photo taken in a domestic setting, an image featuring the seller's body, a professional catalogue image, or one showcasing professional models.
- Ad Characteristics $_i$: A set of variables representing features of the advertisement:
 - **Price Quintile**: A categorical variable representing the relative price of the product within its category and posting month, divided into quintiles.
 - **Caption Length Category**: A categorical variable indicating whether the listing has no caption, a short caption, or a long caption.
 - **Posting Month**: A control for temporal variations in posting, capturing seasonal trends or other time-related factors.
 - **Condition Disclosure**: A binary variable indicating whether the condition of the product is explicitly disclosed.
- Reputation and Experience $_{j,t}$: Variables reflecting the seller's reputation and activity level:
 - **Log(1 + Reviews at Posting)**: The logarithm of one plus the number of reviews the seller had received at the time of posting, reflecting their historical reputation.
 - **Log(1 + Posted-Sold Difference)**: The logarithm of one plus the difference between products posted and sold by the seller, reflecting unsold inventory.
 - **Log(Cumulative Posted)**: The logarithm of the total number of items the seller has listed to date, capturing their experience level.

- **Brand Characteristics_i:** Variables reflecting the prominence and perception of the brand:
 - **Log(Brand Product Count):** The logarithm of the total number of products listed under the same brand, indicating the popularity or prevalence of the brand.
 - **Brand Perception:** A variable capturing the perceived reputation of the brand.
- **Product Characteristics_i:** Variables describing specific attributes of the product:
 - **Size Grouped:** A categorical variable for product size, with reference group "XS."
 - **Primary Color:** A categorical variable for the dominant color of the product, with reference "no_color."
 - **First Material:** A categorical variable for the primary material of the product, with reference "no_material."

IQA

- **BRISQUE (Blind/Referenceless Image Spatial Quality Evaluator):** This metric evaluates image quality without requiring a reference image, focusing on natural scene statistics to quantify distortions. A lower BRISQUE score indicates higher image quality, making it suitable for analyzing real-world images with unknown degradations.
- **NIQE (Naturalness Image Quality Evaluator):** Similar to BRISQUE, NIQE is a no-reference image quality metric that measures deviations from natural image statistics. It provides a score that reflects how close an image is to the statistical properties of high-quality images, with lower scores representing better quality.
- **MUSIQ (Multi-Scale Image Quality):** This metric evaluates image quality by considering multiple scales and assessing both the global and local features of an image. It is particularly effective for images with complex textures and varying levels of detail.
- **DBCNN (Deep Bilinear Convolutional Neural Network):** This deep learning-based metric assesses image quality using a bilinear architecture, combining local and global

information to predict perceived quality scores. It leverages pre-trained neural networks for robust evaluations.

- PAQ (Perceptual Aesthetics Quality): This metric measures the perceptual aesthetic quality of images, focusing on elements such as composition, lighting, and visual appeal. It is particularly relevant for understanding consumer-facing aspects of product images.
- PIQE (Perception-based Image Quality Evaluator): PIQE is another no-reference metric that quantifies image quality by identifying and analysing distortions such as noise, blur, and compression artefacts. Lower PIQE scores correspond to higher quality images.
- IL-NIQE (Integrated Local Naturalness Image Quality Evaluator): IL-NIQE extends the NIQE methodology by incorporating local image features and naturalness statistics. This metric provides a more granular assessment of image quality, especially for images with diverse textures and content.

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