ABSTRACT

LEPPARD, TOM R. Collaborating with Competitors: Exploring Network Mechanisms that Drive the Benefits of Collaboration in Music. (Under the direction of Dr. Anna Manzoni and Dr. Andrew P. Davis).

Collaborations between workers can have varied impacts on work outcomes. Across multiple industries working in teams or with partners can augment the process of work and lead to higher quality output (Alsharo et al. 2017; Cui et al. 2021; Leahey 2016). Researchers examine the ways collaboration among peer workers operates across multiple settings. Recent scholarship on online teams (Yang et al. 2022), coding professionals (Zöller et al. 2020), and the creative industries (Deshmane & Martínez-de-Albéniz 2023; Diani & Sacchetti 2023) demonstrate that occurrence and benefits of collaboration can be industry specific. In other words, the nature of the industry - including its structure, and how one succeeds in that industry – shapes the way peer workers collaborate and how/whether that collaboration benefits them.

This dissertation builds on research within the sociology of culture and the workplace with emphasis on the music industry by adopting a network perspective on collaboration. As workers collaborate, they generate a network of peers. Leveraging logic from network theory, graph theory, exchange, and interaction, this dissertation constructs a coherent image of how collaboration drives career benefits in music. Across three empirical tests, I focus on theories of network position to explicate the ways that collaborating with others in music positions oneself as central within a genre. Because success in the music industry involves gaining the most popularity from within a genre (see Mark 1998; 2003; Silver et al. 2022) carefully selecting how much and who to collaborate with can position oneself in a more prominent or powerful positions relevant to others. I also highlight the type of collaboration that exists between artists and the context wherein they collaborate as influential in shaping the benefits they receive. Today, as streaming services are the most utilised connection point between artists and their

listeners, collaboration on these platforms involves appearing on profiles. I examine how this industry specific form of collaboration are associated with different pathways to career success. Finally, I explore the role of reciprocal exchange through collaboration and whether reciprocity is a driver of the collaborative connections of artists and their career success.

Findings of this research build on the scholarly understanding of mechanisms that drive the benefits of collaboration in creative industries such as music. In Chapter 4 (Study 1) find that prominent and powerful artists are more successful than others in the group. However, I also find that an artist's success can be diminished through over-embeddedness, or in this case, over-collaboration. Artists must balance their solo identities with their group affiliations, or else the benefits of collaborative centrality dilute. The career success of those who are highly prominent, powerful, or who have many connections to influential others is less than those with low- to mid-range centrality. Next, in Chapter 5, I find some subtle but provocative differences between outgoing and incoming collaborations housed on the profiles of artists using streaming services. I find that appearing on another artist's profile boosts popularity, monthly listeners, and followers, whereas having another appear on the host profile is also associated with having more streams. I theorise that the outgoing collaborations (featuring on another's profile) expands the resource reach of an artist while incoming collaborations (another artist featuring on the host's profile) builds their reputation. Finally, in Chapter 6 I generate a new measure of individual-to-group reciprocity and find that mutual connectedness is not a primary method for success. Rather, I find that members of the group who have more outgoing than incoming collaborative connections to the group ("takers") are both more central and more successful. Chapter 6 shows that the group's validating efforts to collaborate with an artist endows them with career advantages.

This dissertation makes two major interventions in the literature. First, it adds to the network focus of collaboration (Crossley 2008; Deshmane & Martínez-de-Albéniz 2023; Diani & Sacchetti 2023; Gleiser & Danon 2003 Hodson 2016; Smith 2006; South et al. 2020) by leveraging network theory (Borgatti 2005; Borgatti & Everett 1992; Wasserman & Faust 1994) to describe the ways that collaboration influences success in music specifically. Conceiving a genre as a network of individual artists enables me to examine the mechanisms driving the benefits of collaboration on career success in terms of network centrality and couple a robust literature on the career benefits of social networks (Granovetter 1973; Burt 1995; Lin 2001; Podolny & Baron 1997; Uzzi 1997) with the career success in the creative industries. Operationalizing collaborations in terms of incoming, and outgoing connections between artists in the genre enables me to leverage network measures of centrality and conceptualise how themes like social standing (Chapter 4), exchange (Chapter 5), and reciprocity (Chapter 6) can operate among collaboration networks.

Second, it centres industry specific mechanisms as the context for the benefits of collaboration blending the scholarly literature on the sociology of music (Becker 2008; Roberts & Strandvad 2022) with that on collaboration. Streaming services are an understudied context for collaboration in music. This dissertation develops network theories of how collaboration influences career success on streaming services. Specifically, it demonstrates that artists form a network as they feature on each other's profile. Studies throughout the dissertation demonstrate the importance of the network structure, context, and relationships among workers when researching collaboration on streaming services.

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Collaborating with Competitors: Exploring Network Mechanisms that Drive the Benefits of Collaboration in Music.

by
Tom R. Leppard

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APPROVED BY:

Anna Manzoni Committee Chair	Andrew P. Davis Committee Chair
Steve McDonald	Michaela DeSoucey

Vaughn Schmutz

DEDICATION

To Lex, my forever collaborator.

BIOGRAPHY

Tom R. Leppard was born in Southeast London, England where he spent his childhood and teenage years. He then moved to Greece for a two-year period before he attended Brigham Young University in Provo Utah. He graduated with a Bachelor’s degree in Sociology and minors in both Business and Nonprofit management. He is the first in his family to attend and graduate from university. While in his penultimate year at BYU he met Lexi who would eventually say ‘yes’ before they tied the knot in 2018. From there, he moved to Raleigh North Carolina in 2019 to attend graduate school at North Carolina State University pursuing his Master’s and Doctorate in Sociology. He graduated in 2021 with a Master’s degree. He and Lex welcomed their daughter Eleni in November 2023. Tom is a quantitative methodologist with a background in social capital. His work blends social network analyst, computational text analysis, and statistical inference. He is interested, primarily, in the role of social structure and individual structural position on people’s life outcomes. The main thrust of his research argues that inequalities influence people’s social network and access to transformative resources like social capital.

The current dissertation appends to his focus on social networks and life outcomes by exploring three mechanisms behind collaborative ties between artists and their success. This project represents a fun opportunity to apply social network approaches to part of Tom’s heritage. Tom grew up in Southeast London during the nascent era of Grime. The case study on Grime music blends two worlds together. Tom’s professional expertise with his personal background.

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environments where I can excel. My family have been among the most influential environments. I could not have done this without my forever collaborator Lexi. Lex, you saw potential in me and encouraged me to apply for graduate school. You have put up with my lows and dragged me through to the highs of graduate school life. To our daughter Eleni, I hope your dissertation smashes this one out the water! Thank you for being such an angel and letting us sleep at night so I could finish this project. You and your mum have encouraged me to balance life with my work and to never lose focus of what matters most. Thank you. I want to thank my wonderful parents who have consistently celebrated every milestone and supported my efforts at every stage of the journey. Thank you for your willingness to engage with my professional development and to give advice at every corner. I have wonderful siblings who have also celebrated milestones with me as well. One final thanks to family goes to my beloved grandparents. You were the trailblazers of our family and every generation since has benefited from your efforts. During this process I have lost two giants in my family. To my grandad and grandpop, thank you for your life's work and example. I have felt your influence and motivation through this whole process. To my surviving Nan, thank you for your weekly calls and encouragement. I could not have done this work, or any for that matter, without you. Thank you all.

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CHAPTER 1: INTRODUCTION

The dissertation is about collaboration and how collaboration influences the career success of musicians in Grime a genre of electronic music that emerged in the UK during the early 2000s. The present section introduces and synthesizes the scholarly discourse and debates surrounding themes associated with the topic of study. It then concludes by discussing the aims and research questions of the three empirical studies in this dissertation.

The Economy, Exchange, and Network of Collaboration

Collaboration, for the purposes of this dissertation is where two or more individuals, or entities work together for economic benefit. Collaborative relationships can be conceptualized in several different ways and there are ways to define collaboration that are context specific. For example, the division of domestic labour between housemates or spouses could be seen as collaboration. However, this dissertation draws from Max Weber's theory of economic action within society, exchange, and networks to frame collaboration and the benefits that come from collaborating.

Max Weber defines economic activity as behaviour that is "economically oriented" or actions that are "primarily oriented to rational economic action… and hence is planfully oriented to economic ends" ([1921] 2019: 143). Therefore, assuming Weber's perspective on planful activity, collaboration in work settings can be described in terms of its economic utility. The assumption is that participants in a collaborative relationship weigh the costs and benefits of collaborating and decidedly (or 'planfully') proceed working together rather than alone. This 'planful' process includes the decision to interact with another and a cost-benefits analysis for all parties involved.

Alderfer (1983; 1998) defines collaborative teams as a group of individuals who are interdependently working toward a common goal. Membership in a team of collaborators constitutes a shared responsibility (although not always equally) of the task and the outcomes of the work. When at work such teams form either by the assignment of employers or naturally as economic actors gravitate toward working with others to accomplish their work (Guimera et al. 2005; Morrison-Smith & Ruiz 2020; Mortensen & Haas 2018). When people collaborate in professional settings they generally agree to work together towards a reward (although not necessarily equal).

Collaborative relationships can also be described in terms of an exchange. When collaborators interact, they exchange resources and skills for mutual benefit. Negotiating a collaborative relationship often involves the exchange of resources like professional expertise (Alsharo 2017), trust, compromising on expectations, and outlining division of labour and recognition (Moody 2004). Since all share the responsibility of the outcome, collaborators must trust that their teammates will fulfil their role. Exchange among economic actors can include exchanging non-economic goods and services (Weber [1921] 2019: 155). Bearman (1997) argues that exchange can occur directly (A→ B), or indirectly (A→B, B→C, C→A). Collaboration is an example of such an exchange because it involves an exchange of capital, skill, or knowledge, for mutual (not necessarily equal) benefit.

Sociological theory of exchange applies to worker collaboration across many industries. For example, professional coders bring with them expertise and skill that then impacts the quality of the product, the proficiency of others, or the productivity of the process. This exchange can occur directly between coders or through shared repositories (e.g., GitHub, see El Mezouar et al. 2019; Zöller et al. 2020). Under this paradigm, the rewards of collaboration are endogenous to the exchange that occurs between actors. In other words, the resources that are exchanged directly generates a benefit, a better end product.

Inherently, collaboration is a social action because it involves, at the very least, a dyad. Therefore, collaboration can also be considered in terms of a network. Like other networks, groups of collaborators can generate culturally meaningful norms and bonds within the group. Exchanging with others can generate solidarity as individual's needs are met directly or indirectly (Bearman 1997; Molm 2010; Molm et al. 2007). Furthermore, working with others can boost affective regard for others in the group. For example, across different industries, studies show that as people work together and reciprocate exchanges, trust, and affective regard for each other are built. (Burt et al. 2022; Carr & Walton 2014; Kane 2004; Whitman 2021; Yakubovich & Burg 2019). In this paradigm, the rewards to the exchange can be exogenous to the collaboration. In other words, solidarity, or affective regard does not inhere to the exchange but it is built *because* the collaborative relationship/exchange exists.

Another aspect of collaboration as a social interchange between people are the roles that are associated with working with each other. The division of labour between workers includes defining the role that one will play in terms of the collaborative relationship. For example, an author on an academic paper may oversee the data collection and analysis while another may oversee aspects of the writing. A group or dyad of individuals assumes an identity as a group as they shoulder responsibility for the project/end goal. In this context, social roles also emerge in team settings and through collaborative connections. Leaders exist because of their connectivity to others in teams. The social contract that exists between collaborators generates roles as responsibilities are divided among participants.

There is often a cost-benefit-analysis that occurs when people decide, or companies decide that workers should collaborate. Like Weber's exchange, collaboration can benefit all parties or unevenly favour one/some over another/others (c.f. Weber [1921] 2019: 156).

Cummings and Kiesler (2005; 2007) discover that projects overseen by more constituents are less well organized and much less productive indicating that collaborative work is not always the most effective. Similarly, studies show that teams have a trade-off between the effort put into the project and the credit received for their work (Bikard et al. 2015; Bozeman & Corley 2008; Leahey & Reikowsky 2008). Furthermore, the issue of crediting the team rather than members' individual efforts means that the division of labour is not always evenly distributed (Alnuaimi et al. 2010).

Collaborative teams are structured and function differently, and therefore collaborative relationships can come with varying costs and benefits. For example, authors on an academic paper may exchange human capital or knowledge but receive unequal reward through different authorship ordering (Endersby 1996), whereas those who code through GitHub, or salespeople in teams, may share more equally in accolades or profits gained. Thus, it is important to consider the context and circumstances of collaboration when studying the reasons why people collaborate and the processes by which teams form, individuals interact, exchanges occur, and collaborative relationships evolve. One such consideration is when people choose to collaborate in competitive environments.

Another element of Weber's concept of economic action through exchange is that of the competition of collaborative relationships. An individual's procurement of resources, or acquisition of economic advantage, according to Weber, involves a competition over scare or finite resources ([1921] 2019: 155-157). Economic actors can only exchange resources that are available on any given market. A competitive environment, by definition, means that individuals must achieve over others to succeed. In other words, individuals or teams must outperform others to procure resources or acquire market advantages. A simple example is food or beverage companies aiming to dominate market share by outselling their competitors and garnering the biggest share of consumers.

Collaboration in such an environment encourages actors to get ahead of others and to hold the competitive advantage over them and selective collaboration can be a sure way of maintaining leverage over competitors and obtaining a competitive edge. Uzzi (1997) captured such a phenomenon from a reticular group of entrepreneurial firms. Firms with actors who held strong bonds to important constituents (like suppliers) and built trust with them gained access to fine-grained information and even advantageous arrangements like forecasted opportunities or innovative solutions. This provided them a competitive edge over competing companies. In this study, clothing companies who remained embedded in webs of relationships with influential constituents became more efficient than companies who did not. However, paradoxically, an extended period in dense reticular relationships reduced innovation and limited the flow of new information.

This dissertation frames collaboration as a social economic activity between actors. It draws heavily on themes outlined above associated with economic benefit, networks, exchange, and competition. I focus on a case within the music industry and as such leverage these themes to contextualize collaborations between musicians in terms of exchange and competition for popularity. I maintain that the collaborative connections between artists construct a network of individuals who, together, form a collective or genre. The next section outlines the theoretical framework of music as a creative ecology furthering the Weberian principles of economic action and competition by discussing how collaboration operates in such an environment.

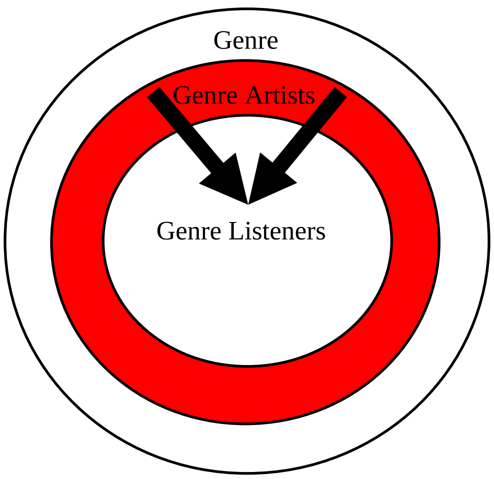
Collaboration in Creative Industries: The Competition of Creativity

In the music industry, collaboration can take various forms. For example, collaboration could occur between record companies and artists, producers and artists, DJs and artists, or artists with other artists. The sociology of music literature predominantly looks at collaboration as individuals creating and conforming to group standards to generate authenticity and signal legitimacy in cultural niches called genres.

Collaboration in music is important to understand in part because the music industry is highly competitive. Namely, in competing for music listeners, musicians are a prime example of workers whose success relies on their dominance over others in their field. Building on the Field theory of Bourdieu (Swartz 1998), and the arts worlds of Becker (2008), modern sociologists argue that the industries associated with art, and the organization of the arts is akin to "creative ecologies" wherein artists gather into small relevant groups and these groups compete with others for the consumption of their products (c.f. Godart et al. 2023 Roberts & Strandvad 2022). While Becker (2008) demonstrated that the creative industries is comprised by multiple interacting constituent parts to produce art and entertainment, this new perspective highlights that success in this industry relies on the successful attraction of the majority of art consumers. Therefore, individual constituents whose success relies on consumer attraction compete for dominance in their part of the art world. An example of such a case is within music genres.

The construction of genres follows a pattern of creative ecologies. Musicians are in competition with other musicians for music listeners. Specifically, the music industry is organized by social niches of music genres and genre listeners. Building on the concept of homophily and propinquity (McPherson 1983, Simmel 1955), Mark's (1997; 2003) work demonstrates that music listeners tend to group with similar others that listen to the same genre. Further, that the structure of the music industry follows a competitive, ecological pattern with individuals (artists) competing over pools of resources (listeners). In Figure 1 I visually represent the three most basic elements of a genre. The first ring consists of the musicological boundaries of the genre. The second consists of the artists who conform to those conventions and engage with creating music of that genre. The third ring includes the listeners of the genre who follow and consume the music of genre artists. This visualization demonstrates that musicians compete with other musicians for music listeners of their genre. While consumers and artists may listen or create music that fits in multiple genre boundaries, this competition is sharpest within the niche of a genre as genre artists compete for small pool of genre listeners.

Figure 1: The Conceptual Structure of a Genre



The time of a music listener is not typically limited to listening to one genre, nor is their taste. Artists are not fully beholden to the conventions of their genre. Some artists introduce both unconventionality into genres and span multiple genres of music by performing multiple forms. However, artists must balance their unconventionalities with the tight boundaries and expectations of their listeners or suffer a loss in popularity (Lena 2014; Silver et al. 2022). While a listener's time is not limited to one genre or one artist, success in the music industry still relies on an artist having the largest following which means that more people are spending time listening to their music over another's. Therefore, the balancing act of musical conventionalities and attracting the most listeners are the foremost important pathways to success in the music industry.

Despite this, musicians collaborate and rely on one another for the continuation of their genre. Early scholarship on collaboration in the creative industries highlights a slightly nuanced, more indirect, or symbolic form of collaboration – imitation. Beginning with Peterson's (1999) exposition of country music, a vein of literature has emerged that examines the ways in which artists "band together" (see Lena 2014) using conventionalities that are associated with their genre. The argument is that artists of given genres signal their authenticity by mimicking the conventionalities associated with the musical characteristics performed by other artists in that genre whilst introducing new elements to form their own unique sound (Lena 2004; Lena & Pachucki 2013; Silver et al. 2022). Thus, genres of music emerge as artists collaborate with one another by conforming to conventionalities associated with that genre of music.

Additionally, scholars have unearthed further symbolic and indirect collaborative behaviours around storytelling and references in the music industry. Gibson's (2014) work on the St Louis rap scene demonstrates artists draw on collective memories to generate their music and present a cohesive story for their genre. Similarly, from a network perspective, scholars trace the way that U.S. Hip-hop artists reference others in their genre through call outs or shout outs in their songs. Hodson (2016) finds that over time artists like 2pac become more and more notorious as rappers throughout the genre reference him in their songs. Collectively these studies demonstrate how collaborations and collaborative behaviours can operate in many ways and, while doing so, generate genres of music with boundaries of authenticity, shared memory, while bolstering the success of both the group and individuals in it.

More recently, some scholars have turned to social network analysis to examine more traditionally defined collaborations (working directly with another artist) among musicians. Using data from Spotify, for example, South et al. (2020) explore how the connectivity of artists to other well connected artists changes at various levels of popularity. They also demonstrate that the density of collaborative relationships between artists differs greatly across genres. Rappers operate in- dense networks of collaborators while other genres like classical music are less collaborative. Furthermore, McMillan (2022) uses a network perspective to examine the gender composition of collaborative ties from popular R&B/hip-hop artists and find that female artists tend to fill peripheral positions in the networks compared to more central male counterparts demonstrating the salience of network structure and position in the creative industry.

The current dissertation furthers the work from recent scholars (see Deshmane & Martínez-de-Albéniz 2023; Diani & Sacchetti 2023) by adopting a somewhat traditional perspective to collaboration in the creative industry (artists working together on songs) and applying a more novel network perspective to examine three potential mechanisms that drive the career benefits of collaboration for artists in a genre. The following section outlines the framework for the empirical tests performed in this dissertation.

Current Dissertation

The current dissertation explores collaborative networks and applies three approaches to studying collaboration in music. First, I apply the lens of structural embeddedness (Granovetter 2017) and examine the network position artists hold in their collaboration network. Second, I adopt an exchange perspective to collaboration in music (see Alsharo et al. 2017; Leahey 2016; Lin 1999) and theorise how streaming services facilitate the exchange of resources through collaborations in music. Third, I turn to the literature on the reciprocity of collaborative connections (Molm 2010; Uzzi 1997) and examine the role of mutual connection in determining one's career success. Ultimately, these approaches constitute three potential mechanisms that drive the career success of collaborators in music. The aim of the dissertation is to construct empirical tests to determine whether these three mechanisms are associated with an individual's career success in music.

Studies in this dissertation build on the literature on collaboration, music, and networks by focusing on three themes: network position, the context/type of collaboration, and an artist's reciprocal exchange relationship with the genre. Specifically, it examines the career success of artists in terms of who they collaborate with, how they collaborate with others over platforms, and whether they reciprocate collaborations with their group. Across three empirical tests this dissertation fills gaps in the music, collaboration, and network literatures where little has been done to truly explore the mechanisms that drive the benefits of collaboration in music. It also centres the streaming services as key to facilitating the benefits of career success. Finally, it proposes a unique measure of in-group status borrowing logic from social network analysis (Wasserman & Faust 1994), reciprocal exchange (Bearman 1997; Molm 2010), and identity-building (Donnely & Young 1999; Mead 1964).

These studies draw on multiple literatures and intersect multiple methodological approaches, key among which is applying the social network perspective to interactions among people. Social network scholars are interested in how resources diffuse throughout networks of people generating benefits for individual participants and the group (Gamper 2022; Lin 1999; Vonneilich 2022). In terms of collaboration, therefore, the interactions between teammates, partners, and collaborators constitute a network where the actors are the nodes, and the collaborative work are the ties. As resources are shared between collaborators they may benefit individually or collectively through improving the quality of the final product, or through streamlining process productivity (Alsharo et al. 2017). In music, collaborative networks serve to draw genre-defining boundaries (Crossley 2008; Hodson 2016) and share talent across groups (Gleiser & Danon 2003). Finally, as artists collaborate with each other, the collaborated upon songs tend to attract more listeners on radio sets (Deshmane & Martínez-de-Albéniz 2023). It is this focus, career success, that the three studies explore in detail by examining potential mechanisms that drive the career-related benefits of collaboration in music.

The first mechanism explored is embeddedness operationalised in terms of the network position that people fill within their group. Second is the type of collaboration between artists on streaming platforms. Third, the reciprocity of collaborative connections between artists and the genre. In broad terms, the empirical tests in this dissertation ask three questions. First, how does network position influence one's success? Second, how does the type of collaboration between artists influence their success given context of their collaboration (streaming services)? Third, do artists who reciprocate collaborations perform better than those who do not?

To answer these questions, I turn to a Genre of UK-based rap music called Grime. Grime is a genre of music that emerged from East London in the early 2000s and has since received global recognition. I discuss Grime in detail in Chapter 2. In what follows I introduce each empirical test briefly connecting it to the background literature discussed above.

First Empirical Chapter: Embedded in Grimy Networks

The first study tests how network position, specifically, centrality, influences an artist's career success in music. Network scholars show that different positions within a collaborative network can provide advantages to workers that boost their success over others in their network (e.g. the competitive advantage of filling a structural hole, see Burt 1995). However, the network perspective on collaboration alludes to the paradox of being overly embedded in collaborative networks. Uzzi (1997) finds that being over-embedded in a collaborative network deteriorates the benefits behind collaborative ties. Specifically, that it leads to a flow of redundant information, an erosion of trust, and an overdependence of one entity on the other.

In music, the current focus of musician success focuses on how collaboration augments an artist's success because of the trade of resources. As musicians work with each other, the song they produce benefits from the shared skills and often performs better on radio platforms (Deshmane & Martínez-de-Albéniz 2023). The argument behind this is that both artists' pools of fans listen to the song, and this drives its success on streaming platforms like Spotify. However, little has been done to fully exploit the potential of the network perspective of collaboration and how network centrality influences success in music. The first empirical study (Chapter 4) conceptualizes three ways that network position may influence one's success in music. First, it conceptualises the degree centrality in terms of an artist's prominence in the genre. Prominence in the genre through the degree of affiliation may boost an artist's success since they are viewed as the prototypical artists or most popular artist to work with in the genre and therefore consumers of the genre may flock towards them. Second, it theorises betweenness centrality in terms of an artist's power over the collaborative network. Exerting influence over who works with whom in the genre and being in the middle of multiple collaborative partnerships may boost an artist's listening because listeners perceive them as powerful influencers over the genre. Finally, it explores eigenvector centrality in terms of a halo-effect (see Thorndike 1936) of collaborating with prominent others. If highly connected artists are more successful than those who are less connected, then their connections may also share in the success. Collaborating with a highly connected alter might boost the focal artist's success since the popularity of the alter may spill over to them. This study also explores the potential for over-embeddedness in music collaborations by testing whether there is a similar inverted u-shape relationship between collaborative centrality and career success in music as there is in other industries (see Uzzi 1997).

Research question 1: How does network position influence success in Grime music?

Second Empirical Chapter: Streams of Collaborators

The second study centres platforms as facilitators behind the benefits of collaboration in music on career success. Technology has driven the formation of collaborative teams across myriad different platforms, each has some unique characteristics or mechanisms through which collaboration influences the performance or success of teams. For example, in e-sports teams are often randomly assigned and benefit from shared levels of control through frequent interactions between team members (Mora-Cantallops & Sicilia 2018; 2019). Meanwhile, professional coders work through repositories such as GitHub and benefit from close proximity to the task and clear procedural instructions when making pull requests (El Mezouar et al. 2019). Likewise, on music platforms, scholars find that exposure to algorithms through playlists are a key driver of success because appearing on multiple playlists that are algorithmically advertised to many listeners boosts the exposure and listening pool of musicians (Aguiar & Waldfogel 2021; Morgan 2020; Pichl et al. 2017; Prey et al 2022; Siles et al. 2022). However, few studies have conceptualised the mechanisms of music platforms in terms of the direction of collaboration that they facilitate.

This study tests the directedness of collaborations on career success in music and theorises how the direction of collaboration can be explained in terms of resource expansion and reputation building that comes from the nomination of peers. Borrowing from Wasserman and Faust’s (1994) logic of outdegree and indegree connections being conceived as expanding ones reach through outdegree ties or boosting popularity by the nomination of others through indegree ties, this chapter explores how this may operate in music. An outdegree collaboration is operationalised in terms of appearing on the profile of another artist on Spotify. This can be conceived as expanding one's resource reach since the listeners of the host artist may also listen to the music of the featured artist. An indegree collaboration is operationalised in terms of having other artists feature on a host's profile. This can be conceived as a reputation nomination of other artists. Nomination, in this instance, means that the featuring artist signals the host as a member of their group worthy of their time. It could be conceived in terms of adding to the host's authenticity as a genre participant (see Peterson 1999). Having others nominate them brings with it the power of the featuring artist's name which may, in turn, boost the host's notoriety and therefore success.

> Research question 2: How is the type of collaboration on streaming services associated with career success?

Third Empirical Chapter: Givers, Takers, and Reciprocators

The third study theorises a way to operationalise an artist-genre reciprocity through collaboration. Reciprocity in network studies focuses on the mutual exchange between dyads within a network (Holland & Leinhardt 1976; Baldassarri 2015; McMillan et al. 2022). Specifically, the balance of the exchange means that if a tie is sent from node i, it is returned by node j. At the network-level, measures of reciprocity capture the extent to which the ties in the group are mutual. Meaning, of the possible mutual connections between each dyad in the network, how many of the observed ties are mutually connected. Such measures, even at the network level, focus on the dyadic relationships that exist among individuals and adopts the sociogram approach of people's social relations, meaning that people are connected to other people. While this atomic perspective precisely captures the extent to which mutual connections occur, it is limited. Fundamentally, people may not have mutual connections at a dyadic level, but at a group level their efforts may be mutual. Pescosolido and Ruben (2000) theorise a more abstract, less atomic method of measuring people's connections. They argue that people's connections to others can be thought of in terms of a spoke wheel or relations whereby the hub, the ego, is connected to large groups bounded by their social context. This offers an interesting opportunity to theorise a new perspective on reciprocity in collaboration.

This study leverages Pescosolido and Ruben's (2000) perspective on social relations by abstracting people's collaborative relationships to the group-level. In other words, each node can be considered the hub or ego of the wheel of relations and the rest of their connections as their group to whom they are connected. In this manner, this study explores how reciprocity may operate under such a structure and theorises that any outdegree from the ego signals their willingness to participate in the group and any indegree received by the ego from any in the group constitutes validation of their participation status. The study then builds a ratio level between an individual's outdegree collaborations and their indegree collaborations and generates four groups based on the results: first, a giver who has more out than in, second, a taker, who has more in than out, third, a reciprocator who returns each they receive and has each they send returned, and fourth, those who have no ties to the group whom I deem solo artists. The study showcases how to leverage the method and provides examples for its empirical utility by applying it to the ongoing theme of career success in music.

> Research question 3a: Can we identify the level of investment that an artist makes into their genre by exploring the reciprocity of their collaborative ties with others in the genre?

Research question 3b: Is the extent to which an artist is mutually connected to the genre associated with their career success?

To answer these research questions, I collected data from a genre of music called Grime. The next section introduces Grime as a case study followed by a description of the processes I used to procure and analyse these data.

CHAPTER 2: GRIME AS A CASE

This dissertation uses Grime music as a case study to explore collaborative networks of a genre. Grime is a UK-based form of rap music that emerged in the early 2000s. This section outlines some of its history, the characteristics of the genre, and its evolution that make it appropriate for such a study. It also presents some descriptive network characteristics of the collaborations in Grime music and the network of grime related musicians. The aim of the current section is to present the genre as worthy of a case study and germane for social network research.

Case-based research such as this is common among studies of social networks (see Granovetter 1973; Uzzi 1997). Cases provide interesting microcosms of networks that when studied closely can produce knowledge that can, in turn be applied to or tested by a broader base. However, the extrapolations made from case-based research are bounded by the degree to which the case is representative of broader trends. Thus, an ongoing line of scholarship emerges to confirm or disconfirm the findings driven by case-based research. One of the most notable is perhaps Granovetter's (1973; 1995) study on getting a job which has precipitated a multitude of other studies aiming to confirm or disconfirm the validity of the strength of weak ties argument (Bian 1997; Gee et al. 2017; Kim & Fernandez 2017). Thus, the current dissertation accepts the limitations of case-based research with the promise of future scholarship angling to discover the validity of its application across contexts.

Social networks methods in music are neither a new nor a novel technique (Crossley 2008; Deshmane & Martínez-de-Albéniz 2023; Hodson 2016; McMillan 2020; South et al. 2020). However, what follows describes Grime as a case worthy of study and explains what can be gleaned from an in-depth case-based approach. The most adjacent study to this dissertation is Crossley's (2008) case study of the emergence of the UK Punk Scene. In this study Crossley leverages archival data to construct social networks and compares those networks as the Punk scene develops. Similar to Crossley's work, the studies in this dissertation flesh out the collaborative ties between artists and test their effects on driving their career success. I follow similar patterns of web-based and book-based archival data collection to ensure the data are representative of the genre.

The History of Grime Music

Several academic and popular culture writers give a detailed history of the emergence of the Grime scene in London (Barron 2013; Hancox 2019; Target 2019). Some of which is pertinent to the content of this dissertation. Grime stemmed from East London in the early 2000s. East London is typically characterised by high poverty (Leeser 2021), large percentage of homes being subsidised by government welfare (Hill 2014) and working-class communities. However, the mainstream music scene there at the time followed narratives of urban life focussing on parties, sex, and money through the likes of UK Garage group So Solid Crew and others. The incongruity with the music scene and the lived experience of East Londoners drove the desire to revolutionise the music scene to make it representative of life in London.

The original artist of Grime, Wiley, broke away from the garage scene and formed a collective or crew called Pay as You Go Cartel. This group began experimenting with Garage music and introduced what became the twilight song of Grime - "Know we" released in 2000. From this, the Grime scene branched away and Garage atrophied. Most of the Grime scene remained underground with impromptu shows, pirate radio sets, and unofficial music videos being posted to online platforms like ChannelU (Hancox 2019; Target 2019). The scene burgeoned, despite police and politicians trying to shut it down for its alleged gun culture (Duggins 2016; Fatsis 2019; Hancox 2019). Throughout the early 2000s, more artists joined, and the Grime scene gathered momentum. In 2003 Dizzee Rascal was the first to release an album, *Boy in Da Corner* which saw both subculture and mainstream success.

Into the late 2000s and throughout the 2010s Grime garnered a massive following throughout the UK with artists appearing in Manchester and other parts of the country. Despite being from outside London, the lived experiences expressed through the music knit together a cohesive story of government negligence, failed social institutions and poverty. Akin to Gibson's (2014) study on the Missouri rap scene in the U.S., artists across England produced music under the conventions of the Grime genre representing the struggles they face in their areas. Today, Grime has reached global notoriety but has attempted to maintain its grassroots culture through platforms providing novice rappers across the globe a chance to perform (see International Grime - Youtube).

Scholarship and journalism on Grime offer more insight into history of the genre (Hancox 2019; Target 2019), its musical characteristics (Charles 2018; 2019a; 2019b), and the lived experiences of its artists (Barron 2011; Collins & Rose 2016; Dedman 2011). The following sections briefly discuss multiple elements of Grime and frame it as a case worthy of the dissertation.

Grime as a Genre

Grime is a form of rap music that stemmed from the Jamaican scene in East London. Grime music is characterised by a heavy beat, fast pace, and frenetic energy. Musicians proudly rap over instrumentals that range from 138 to 140 beats per minute with 140bpm as the standard. This musicological characteristic, alongside the slang used in the songs is a definitive trait of the music (MasterClass 2021) that are often used to differentiate itself from other genres (see Hot

97). Listening to Grime music there are obvious references to Jamaican roots with the use of Jamaican slang and reggae-like rhythms.

Beyond the characteristics of the songs themselves, there are also multiple genre-defining ordinances that make Grime an interesting case. Charles (2019a; 2019b) explored the raves, freestyles, and other elements of Grime music performance and found clear connections to Jamaican dancehall culture. As discussed below, other characteristics of the genre are that Grime is both collaborative by nature and very competitive; collaborative by way of many artists being involved in song-making, radio performance, and live shows, and competitive through the clash culture that it encourages whereby artists prove dominance over others in many ways. Thus, the content of Grime music will often include the voice of multiple artists or will be directed at another artist.

Grime as a Voice and a Platform

The content of Grime music, according to scholars, can be described as ethnographic because it reflects the working-class livelihood of many in East London. Barron (2013) argues that the content and structure of the music reflects the life in inner city London. It provides a voice for a neglected population steeped in racial and economic inequality and has garnered a reputation for being politically charged speaking on topics of immigration, racism etc. (Charles 2018a). The music, therefore, is designed to reflect the social context of the artists (Charles 2018b) providing a voice for those who are underrepresented in mainstream media. For example, it is common for Grime artists to be first- or second-generation immigrants and their music reflects the lived experience of such communities in London. Furthermore, the genre provides a voice for working class young people of multi-ethnic and -racial backgrounds and generates to a platform to express their lived experiences of poverty, racism, and ethnocentrism in the UK.

Nah, that's not me

Act like a wasteman? That's not me

Sex any girl? Nah that's not me

Lips any girl? Nah that's not me

"Yeah, I used to wear LV

Put it all in the bin cause that's not me

True, I used to look like you

But dressing like a mess? Nah, that's not me

You see me, I come from the roads

You wanna try and put Skepta on hold

But no, badboy I've been one of those

Wake up call, you will get one of those

One to the eyeball, one to the nose

I don't really care about your postcode"

Skepta ft. JME – That's Not Me

Grime gave a voice to many in London and across the UK whose lived experience was not represented in mainstream music. Much of the contemporary rap and pop music of the time reflected the mainstream ideals of money, sex, and popular culture. Meanwhile the grittiness of Grime music reflected the lives of those in London. The lyrics above demonstrate the incongruence between the lived experience of those from East London with the mainstream music. In this excerpt, Skepta's rap shows that life in London isn't about sex and chasing women, but rather about struggle and even violence. Being "from the roads" means that they do not have the luxuries of wearing designer brands and womanizing. This song strongly positions Grime music in opposition to the mainstream music of the time.

"*It ain't about the tea and biscuits, I'm one of those English misfits,*

I don't drink tea I drink spirits, and I talk a lot of slang in my lyrics,

These goes a horse, horses for courses, nah more like corpses on corners,

And Stafford shire Bull Terriers and late night crawlers,

Police carry guns not truncheons, make your on assumptions,

London ain't all crumpets and trumpets, it's one big slum pit."

Lady Sovereign – My England

The lyrics in Grime music provide a narrative of violence and struggle that reflects the lived experiences of many in London. Drawing from songs like Kano's 'London Town' and Lady Sovereign's 'My England' Barron (2013) demonstrated that these artists represented the working class lived experience. The above excerpt from My England juxtaposes some of the affectionate stereotypes of English culture with the harshness of inner-city realities of slang, spirits, guns, and violence. Grime exposed what could be considered the underbelly of British culture. The gritty side of inner-city London that goes beyond the romantic stereotypes and into the lived experiences of the city's poor.

"Wanna know why I'm angry?

Back then they took our mandem and hang we

Left black women abandoned with families

Now we run the kids from the block til' they're athletes

Yeah, but it gets a little deeper

They link black skin with crack, guns and dealers

Violence, crimes, while we buy the sneakers

A stop and search is standard procedure"

Shystie – DBT Remix

The genre highlighted not only voices of the working-class, but also to those who experience overlapping inequalities. The above lyrics speak about issues associated with race like mass incarceration, and the over-policing of Black communities in London. Assumptions of Blackness tied with drug use, violence, and crime influences the lives of Black people in London. The artist, Shystie, a Black woman, speaks about having to raise children due to the disproportionate levels of arrests on Black males. Grime music gave the working-class, non-White communities a platform to be heard and tell of their lived experiences.

Second, Grime provides a platform for political change. Beyond simply alluding to the social problems associated with life in London, Grime artists have used the lyrics of their songs, and the fame derived from music to demand and effect political change. Across multiple songs, artists discuss issues ranging from wages, immigration, and conflicts overseas. Many of the themes associated with these songs surround greater representation and equality for minority groups throughout the country and across the globe.

Grime artists, therefore, are not just musicians who generate music for success, but are actively engaged with representing life in the inner city. Their music highlights the oppression of urban communities and argues for the liberation of all people. Charles (2018a; 2018b) claims that artists are intellectuals who assume a role to represent people within their social sphere to leverage political power. The movement of Grime for Jeremy Corbyn demonstrates the type of grassroots efforts that Grime artists take on to promote a political party and even influence the policy makers opinions on social issues. Famously, Grime artist JME met with Jeremy Corbyn to discuss voter turnout (O'Connor 2017a; 2017b).

Culture Vultures and Pagans.

Entering the mainstream of the music world has meant that Grime garnered the attention of the world stage. Voices from a grassroots genre coming from an impoverished part of East London have now experienced worldwide notoriety and attention. Artists within the genre have tried multiple times to ensure its nature does not change. Collaborative efforts from outside the genre have made this effort difficult. One such case of this is the collaborative ties between popular mainstream artists like singer-songwriter Ed Sheeran and Canadian rapper Drake with Grime artists. The following excerpts demonstrate the struggle to balance the genre's roots with its growing notoriety.

> "Although our names were firmly attached to grime, the music that was bringing these huge new audiences was doing little to promote the original 140bpm gritty underground sound" (Target 2019, p.242).

> "Grime in its purist form was suffering at the hands of the mainstream, as so many artists temporarily ditched the 140bpm tempo for something a little less hard and fast that could be support cross the board… grime needed a revival…" (Target 2019, p.247).

> "**We built this up, that's why we must protect it, If suttin' ain't right, we must correct it**, On a daily basis, pay attention to the brand, We got the deeds and we own the land. Still Wiley, but now it's all 20 years later, My petrol is the fans and the haters, My foundation makes me one of the creators, I am the Eskibeat maker, Dad wanted me to be a baker, But I had different choices to make, So, I fly the flag, the UK music don, Go put my music on, Yo, we done all that now we're moving on, **Next generation, yous are on,**

I'm all eras, I wanna know who's a don, They say you can't do it, better prove 'em wrong, We got bare opportunities to get bread, My brudda, don't lose your head, Use your business brain, it's like shottin', **But now it's just music culture we're shottin'**" (Wiley, Protect the Empire).

Wiley, considered the Godfather of Grime, has made several contributions to the resurgence and redefinition of the genre throughout its evolution. The above excerpt from his song *Protect the Empire* demonstrates his core role in maintaining the connections to the genuine roots of the genre. One of the main roles he emphasizes is protecting the boundaries of the genre from outside influences. In several instances, he has been critical of "outside" artists for allegedly using the new wave of success in Grime to better their own career. He claims that such people are 'culture vultures' or 'pagans.' By this, he refers to their tendency to flock towards the genre when it is successful to benefit from its success. What follows are several quotes from an interview from Wiley about Ed Sheeran's and Drake's success and their relationship with the Grime scene.

"Drake is a Pagan; Drake is a culture Vulture. Ed Sheeran, you are a culture vulture… The other day, mate, you had to use Grime to tip your song over the edge… Ed is not a Grime MC… You're not allowed to use Grime, you know why? Because we aren't allowed to use you." – Wiley

"Ed is worth 160 million… if Ed was there in Grime, none of that 160 million has gone anywhere near Grime… Artist, stay away from culture vultures." – Wiley [emphasis added].

"Mandem, who are not from the hood try to get involved with man from the hood… He is not embracing the scene he is doing it for himself." – Wiley.

(Darville 2019; Just Bored 2019).

These quotes demonstrate the protective nature of Grime artists over the genuine roots of the genre. To reconcile mainstream success with the gritty realistic genre it began as, artists like Wiley have made attempts to draw Grime back to the original roots. Dizzee Rascal, another central artist to the genre, has also moved on this by publishing a song called “grime ain’t dead” which hearkens back to the roots of the genre. Such efforts demonstrate the role of collaboration over time in influencing the nature of the Genre. The example of Drake and Ed Sheeran demonstrates the role of outside influence interacting with the boundaries of the genre. Collaborative efforts between Grime and non-Grime artists, according to Wiley, ultimately decouples the genre from its roots.

The Grime genre, however, goes beyond the musicological structure and performances, it involves the people who make and participate in the genre. Behind the lyrics and heavy baselines are artists that participate in upholding the character behind the genre. These artists are tied together symbolically through their mutual participation in the Grime scene but also through collaboration and competition. The collaborative characteristic of Grime networks is the focus for the current dissertation.

Grime as collaborative.

> “Grime emerged from a spider’s web of intergenerational influences, school-mates, neighbours, friends, family, and people who knew people…” (Hancox 2019 p. 33).

Despite being embedded in an individualized industry that is structured into competitive spaces where genre-artists compete for genre-listeners, Grime, like other rap genres (Deshmane & Martínez-de-Albéniz 2023; Hodson 2016; Light 2014; McMillan 2020; South et al. 2020), is very collaborative. From the beginning Grime artists have been collaborative both musically and socially. Several accounts demonstrate that artists of the nascent genre relied on one another's support to succeed (Boakye 2018; Hancox 2019; Target 2019). Pirate radio sets bounced from one person's flat to another's all over East London. Further, the radio sets used to be filled with multiple artists sharing mic time, collaborating on production and performance. Many of the genre's ordinances involve a group of artists brining the music to life either through live performances or through multi-artist events like cyphers (Charles 2018a; 2018b). Finally, artists used to be bounded into crews or initiatives that would perform together. These features of Grime as fundamentally collaborative genre can still be seen today with many Grime songs having multiple featuring artists.

Grime as competitive.

"Grime is a highly competitive sport. If do not want to be the best, there's hardly any point picking up the microphone…" (Target 2019, p. 215).

Grime is a particularly competitive genre. Like hip hop, dance hall, and others, Grime has multiple formalised elements used by its artists to tussle for genre dominance. Grime has a complex array of direct, indirect, and symbolic ways that artists use to belittle other artists and assert dominance over others. While these are all culturally significant to Grime, that is not the focus of this study. Others, such as the work of Charles (2018), Dedman (2011), and others (Barron 2013) document the musicology and ethnographic significance of such cultural ordinances. The focus of this study paints the artists as professionals and their work in the light of collaborative relationships and examines the effects and instances of collaboration in such a context. On top of its own competitive characteristics, it is embedded in an industry that is competitive and easily definable in terms of its constituents and the desired rewards - musicians of a genre seeking genre listeners for career success. Thus, Grime is an interesting case to examine the influence of collaboration on career success in competitive environments.

Grime as a Network: The Focus of the Dissertation

This dissertation views Grime as a network. Rather than viewing Grime as a genre in terms of its musicological characteristics, the focus of this dissertation is on the structural components of the relationships that exist between artists. The aim is to leverage Grime as a case to explore collaborative networks within a genre of music and the various effects of, network position and topology, collaboration, and group status on career success. The focus of the dissertation is less on the genre characteristics or the cultural and political elements but rather focuses on the artists in the genre and the affiliations between them. As such, the remainder of the dissertation focuses on the characteristics of Grime collaboration networks, and the position that individual artists hold within those networks. This can be conceived of as the people in Networks of Grime and the networks of Grime.

People in Networks of Grime.

Figure 2 shows a visual of the collaborative relationships that exist between the artists. The nodes constitute artists and the edges of this network represent a collaborative tie between the artists from the beginning of the artist’s tenure till the end of 2022. Upon basic visual inspection, this figure reveals that this genre consists of a dense core group of artists who work with each other, and rings of artists coming away from that core. This finding corroborates previous assertions that the UK rap scene consists of culturally core and peripheral groups (Dedman 2011) and extends it into the connections between artists. From a collaborative perspective, this characteristic makes Grime a fascinating case for study to examine how collaboration influences career success, and how this tight core may be the driver of its success.

Figure 2: The Grime Network

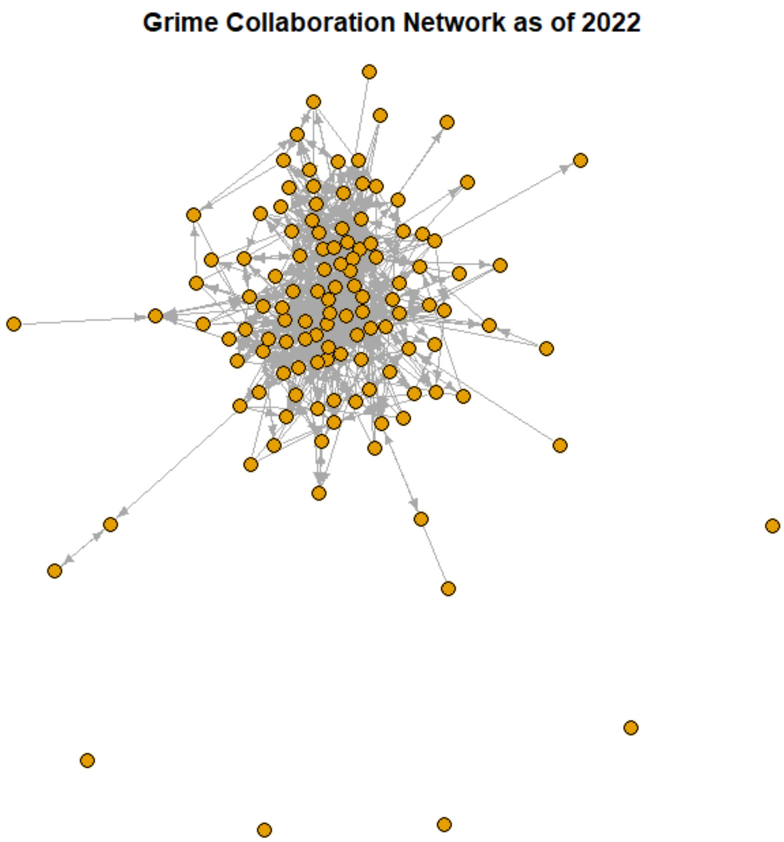
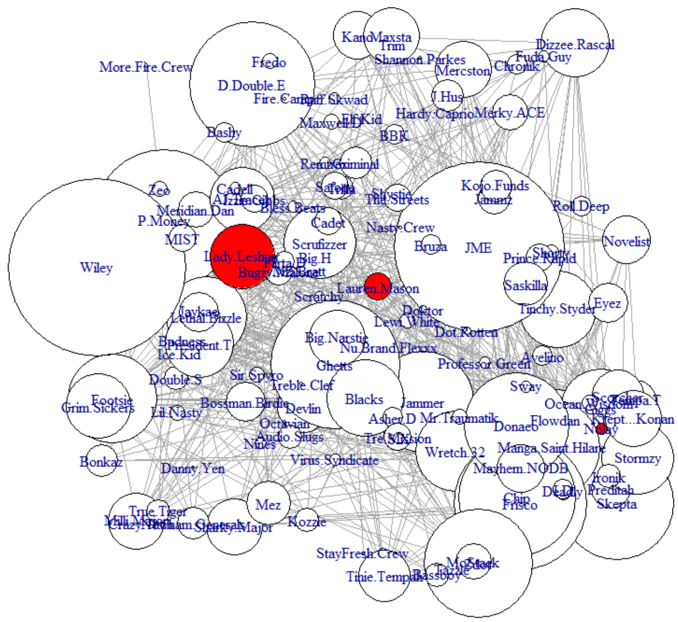


Figure 3 shows both the sex composition of the genre and overlays the degree centrality apparent in Figure 2 to demonstrate the disproportionate distribution of collaborative centrality in this genre by artist sex. The Size of the node indicates the artist's degree centrality score, and the colour of the nodes represent the artist's sex (white = male, red = female). Of the 122 artists in the sample only five are female. Figure 3 demonstrates both this male dominance of the genre, and the subsequent collaborative disadvantage that female artists have in this genre. In this visualization only three of the five female artists are visible due to the node size commensurate to their collaborative degree centrality score. Rap genres are historically male dominated and even misogynistic (McMillan 2022; Weitzer & Kubrin 2009). Figure 3 shows that this extends to Grime.

Figure 3: The Grime Network 2022 Showing Degree Centrality and Artist Sex



Networks of Grime Artists.

In addition to the people in the Grime networks, the networks of Grime artists also have characteristics that make it an interesting case. This section explores some topological measures of Grime networks over time.

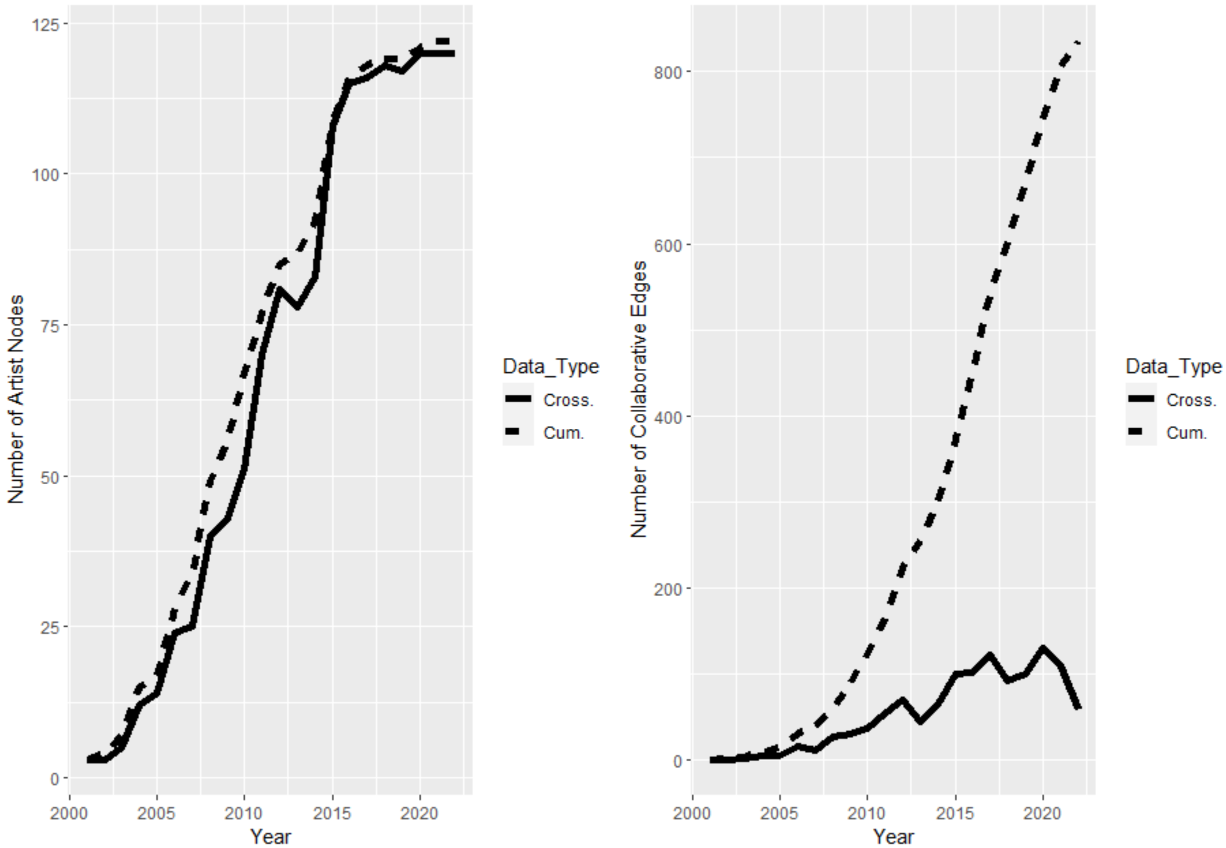
To explore the network characterises of the genre and make inferences on the collaborative relationships within Grime, this section leverages several network-level measures from both cross-sectional and cumulative networks. The cross-sectional data takes measures from the collaborations each year while the cumulative data snowball the previous year's collaborations with the current year. In other words, the cumulative network in 2022 includes all collaborations between artists from 2001 till 2022. This section discusses the growth of the network of Grime artists by in terms of its size, order, density, and cluster modularity.

Size and Order. Network size and order measure the number of nodes and edges in the network. These capture how many artists were active in the genre per year (cross sectional) or by the year (cumulative) and how many collaborative edges were present. *Density.* Density provides a measure of how many collaborative edges exist compared to the number of possible collaborative edges the network has. This measure is used to indicate how connected/interactive the artists are in the genre. The denser the network, the more interconnected they are compared to a sparse group. *Cluster Modularity.* Since this is a directed network, the InfoMap community detection algorithm provided the modularity score indicating how distinct the subgroups are within the whole network. A higher modularity score indicates denser packed subgroups within the genre while a lower modularity score indicates more less distinct subgroups. This measure is used to indicate whether the genre remains cohesive or divides as it matures.

The genre grows over time with new artists joining and collaborating with others as it matures. The first line graph in Figure 4 shows that the genre steadily grew between 2003 and 2012. During this period the both the cumulative and cross-sectional data show a sharp growth period from around five artists in 2003 to near 80 around 2012. However, the cross-sectional data demonstrate a retrenchment period for grime for a year until it picks up again around 2014. This mirrors what writers refer as the “renaissance” of Grime music (Target 2019). Towards the later period, however, there is an obvious plateau as the genre matured into the late 2010s where very few new artists joined the genre.

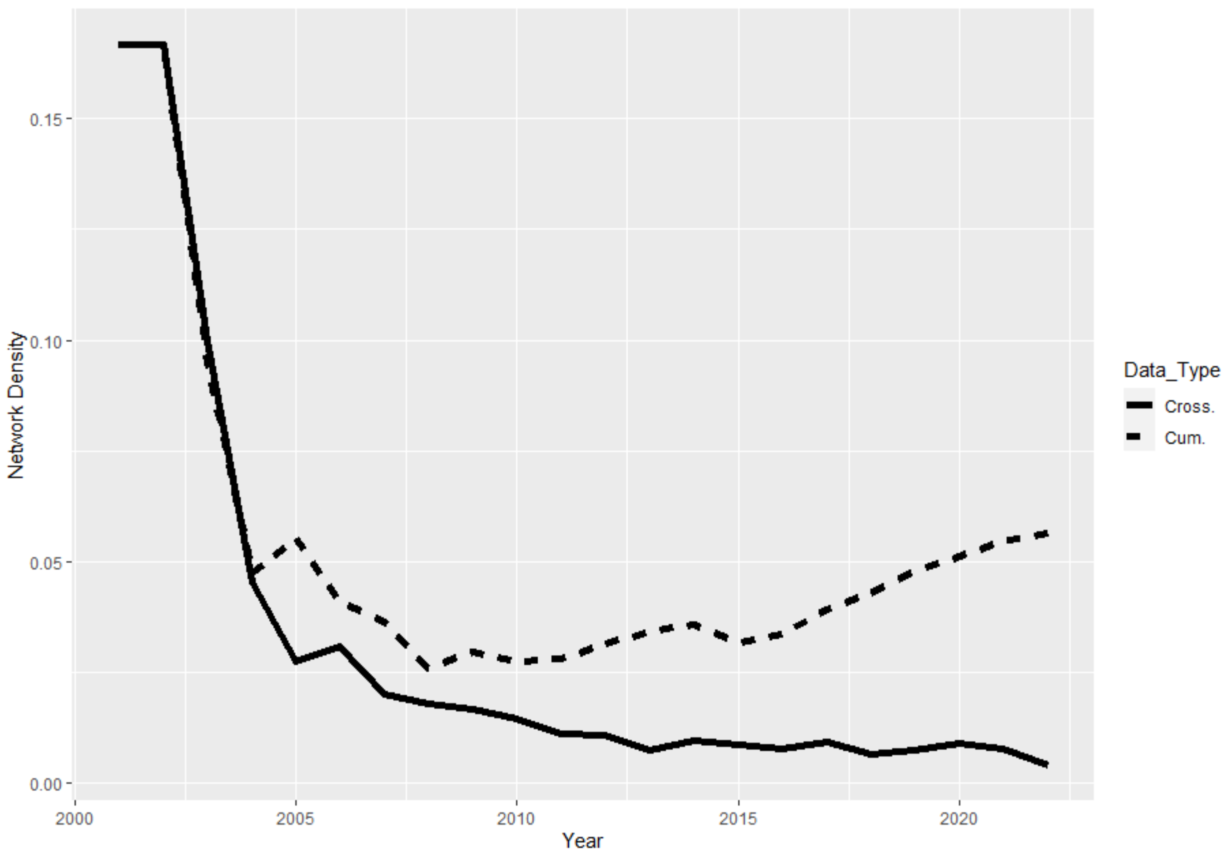
The second graph in Figure 4 shows the graph order which provides a count of the number of collaborative edges in the genre. In this graph, the divergence of the cumulative and cross-sectional data is prominent. It diverges so much because the cumulative data presents an additive effect of each year’s worth of collaborations while the cross-sectional data only presents the number of ties present in that year. In this instance, the cumulative data shows that grime artists collaborative a lot with each other ~825 total collaborations as of 2022. However, the cross-sectional data tell a different story. These data indicate that the heyday of Grime's collaborative connection is between 2010 and 2020 where each year around 100 collaborations occurred between artists in the network. Meanwhile, past 2020, it appears that fewer artists are collaborating with each other as indicated by the declining line. Consider both graphs together, and the story of the early 2020s becomes even bleaker since the most artists are present in the genre during this time, but they are not working with each other. This indicates that perhaps Grime artists have moved on from working with each other and are working with other artists outside the sample, potentially outside the genre. This could indicate an evolutionary period of the genre whereby Grime is, despite the best efforts of some of those central to the genre, moving away from the original network and towards another generation of artists and perhaps music.

Figure 4: Line Graphs Showing Network Size and Order Over Time



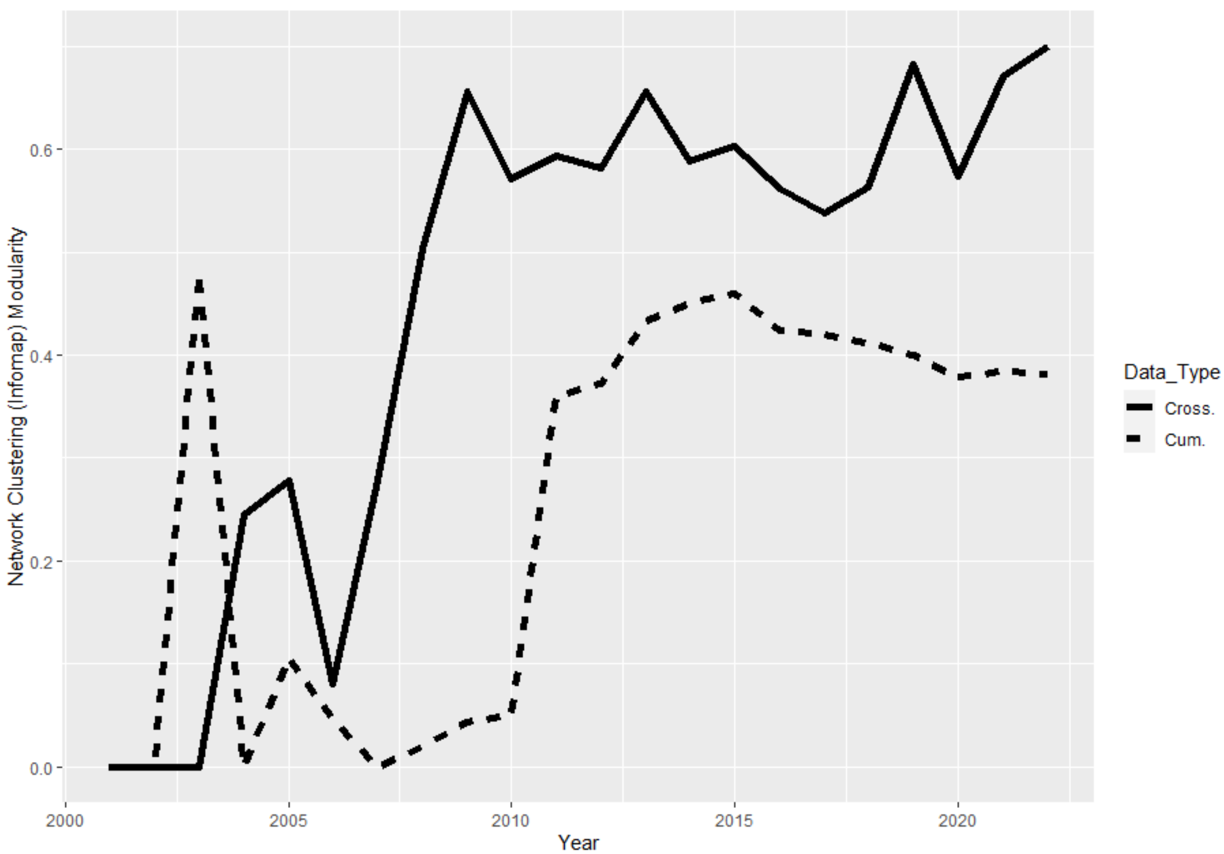
The density scores presented in Figure 5 suggest two distinct stories. First, the cross-sectional data shows a drop in density between 2001 (0.16) and 2005 (0.03) suggesting and a continued but gentle rise in density in the networks from 2005 to 2022. Networks within Grime are becoming sparser over time according to these findings. Meanwhile, the second story taken from the cumulative graph mirror the fall between 2001(0.16) and 2005 (0.06) but diverges from the yearly trends from then on. The cumulative data suggest that density of Grime networks remain consistent between 2005 and 2020 where the density remains between 0.05 and 0.25. After 2020, however, the cumulative networks in 2021 and 2022 have higher density than in the 2010s. This story suggests that networks of grime artists, when considered over time not each year, solidify and vary only slightly over time. However, it is important to note that the density scores are very low to begin with suggesting that networks within Grime are not very tightly connected. However, the measure shows the number of actual collaborations divided by the number of possible collaborations in the network. Thus, the graphs suggest that artists work with each other differently at each time period of the genre.

Figure 5: Network Density Over Time



Over time, Grime artists have become more modular. Figure 6 shows line graphs of the community modularity within the collaboration networks. Both lines indicate churning of modularity throughout the years suggesting that Grime artists were more tightly connected into groups at some times than others. It is important to note that the scores, although apparently vastly different for the pattern of the line, are very low to begin with. This suggests that, although there is some variation, there are only few identifiable subgroups in each year. However, the changes in community modularity allude to the behaviour of artists in the genre. For example, the cumulative line graph suggests that around 2007 there was a spike in communities followed by a period of dissolution before another spike during the early 2010s until the network appears to level off. The cross-sectional line suggests a similar pattern only that the networks in 2010s are modular but churns from year to year. Network density is an important measure because it demonstrates the interactions of artists spanning the whole genre. This measure suggests more of a consolidation than a dilution of the genre because the pockets or communities of in-genre artists have emerged and increased in number over the years.

Figure 6: InfoMap Modularity Score



In sum, the network analysis of Grime suggests that the genre has grown, the number of artists and collaborations has increased both cumulatively and cross sectionally. Although, there is clear evidence for a decline in inter-artist collaboration in more recent years (Figure 4). Further, the density (Figure 5) and modularity (Figure 6) of the graphs suggest that artists interact more with each other over time, but over time the collectives or clusters of artists dilute.

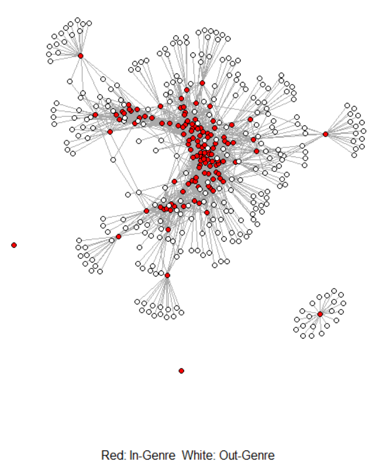
Fans of the Grime Network.

The artists in the Grime networks also act as gateway for their listeners to traverse across the genre. Specifically, Spotify profiles trace the pathways of listeners from one artist to another. The artists in the genre are bounded not only structurally through collaboration, but also through shared listeners. Although not the direct scope of the studies in this dissertation, the dual connectivity between artists of collaboration and listeners demonstrates that the networks of Grime are both structural and symbolic. Considering the fans of the Grime network provides alternate connections between artists that future scholarship can explore. This dissertation takes steps towards seeing genres in terms of the structural relationships between artists. This section also demonstrates that considering a genre as a network opens multiple opportunities for study. In this case, the connections between artists who share fans of the Grime network.

Dedman (2011) documented the culture and the following of Grime music and claimed that the genre consists of those who are at the core and those who are peripheral to the genre. Those ‘purists’ at the core of the genre maintain the groups’ identity, while those in the periphery simply follow the ongoings of the genre. This section uses network data collected from Spotify to visually represent the flow of Grime fans. On an artist’s profile, Spotify has a function where they suggest other artists who fans of the profile’s host also listen to. In other words, listeners of the host artist also listen to the artists that Spotify show in that list. Spotify lists links and images of up to 20 other artists that fans also listen to. This figure shows artists (nodes) connected to other artists by the fans that also listen to them. The direction of the edges indicates that the profile of node i listed node j and so indicates the flow of fans going from one node to the other. The colouring of the graph indicates whether the artists are in or out of the sample. I use it as a loose proxy for in and out of genre artists. Such a network is rich with possibilities for study, but in this section, I discuss what such a graph shows about the fans of Grime.

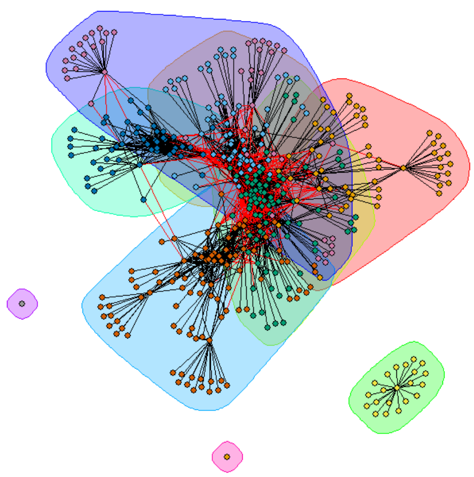
Figure 7 presents fan network data taken from the Spotify profiles of the 122 Grime artists included in the sample of the present study. The structure of the network echoes what Dedman (2011) found that a very dense core exists in Grime music. This network, however, indicates that listeners of Grime music largely keep to a dense core group of artists. The central red nodes in the graph are very densely connected indicating that they share fans. This demonstrates that Grime artists have a dense connection to each other through their fans. Such a pattern suggests that collaboration and competition may have a big impact on who fans choose to listen to. Another element of the graph's structure that is noteworthy are the trees. The trees of the graph indicate that there are fans who enter the genre through certain artists. For example, the bottom left of the graph shows a Grime artist whose fans listen to non-genre artists and genre artists. Such artists play a significant role brokering fans into or out of the genre and such fans might begin listening to Grimes artists through the connections that artists share.

Figure 7: Network of Grime Artists connected by Mutual Fans



The branches of the network suggest that there are fans of artists who listen to groups of other artists. Figure 8 shows a network map with the Louvain clustering overlayed and portrays nine groups of artists that fans cluster around. The modularity score from this test was 0.52 which indicates that these groups are reasonably distinct. Thus, grime artists tend to attract listeners which cluster with listeners of a set group of other artists. This result echoes Mark's (1998) argument that listeners flock together. Measuring the similarities between the artists in these clusters may indicate the differences in tastes within the listeners of Grime music.

Figure 8: Network of Grime Artists connected by Fans with Louvain Clustering



Conclusion

This section has discussed the history of Grime music. Situated from East London, the genre with its collaborative and competitive characteristics makes for an appropriate sociological case of how collaboration in the music industry influences success. This chapter demonstrates the role of a genre influencing the notoriety of lived experiences. It also depicts the ongoing efforts of artists to maintain the cultural boundaries surrounding the genre and how collaborations between in- and out-genre artists may influence this. The current dissertation aims to explore the success of individual artists based on their collaborative connections housed on music streaming services. It centres on themes of identity, and group validation as a marker of status. Grime provides an appropriate case for these and future studies.

CHAPTER 3: DATA AND METHODS

Data

The current dissertation triangulates multiple data science methods to amalgamate data representative of the Grime genre. I used several methods, like web-scraping, and hand coding from Spotify to inform the sampling and analytic techniques. The three empirical tests included in the dissertation stem from the same dataset that follows the collaborations, network structure/position, career success, professional and individual characteristics of 122 Grime artists. In some instances, the data used in models include collaborations beyond the 122 artists in the sample. For example, the network structure and position of artists in the sample from Chapter 4 come from networks which include other artists outside the sample. The results reported, however, follow the same artists across the three empirical tests performed.

Sample and Sampling methods.

There are two main sampling methods used by researchers interested in collaboration and popularity among musicians: the first of which is to use chart information gathered from sources such as billboard.com (Lena 2004; McMillan2022) or repositories for lyrics (Hodson 2019; Smith 2006), and the second is to scrape data from music platforms like Spotify (South et al. 2020). Both approaches have their own strengths and weaknesses. For example, studying the hip hop top 100 list gives researchers a comprehensive list of artists who are popular, however, any inferences on collaboration and career success are limited to popular artists due to the exceptional nature of their sample. Similarly, relying on algorithms from music platforms like Spotify provides a broader net of artists, but may be subject to systematic bias (for example, it may discount legitimate artists because they aren't picked up by Spotify's algorithms). Thus, I triangulated several methods to gather a comprehensive and representative sample of artists.

Grime is a small genre largely based within the United Kingdom. I exhausted six sources to maximise the sample in the current study that use both systematic and purposive sampling methods (see Table 1). Largely, I drew upon archival data and data scraped from Spotify. First, I used the book "Grime Kids" written by DJ Target (2019) who lists several grime crews in chapter 7 and 9. I then searched the crews to draw a sampling frame of artists involved in these grime crews on sites like hiphopdatabase.fandom.com or Wikipedia.com. I wrote down the names of artists in each crew when available which generated a list of 146 artists. Second, I looked at the "Grime Classics" playlist on Spotify and took a list of the 46 artists represented thereon. Third, I used the four volumes of "This is Grime UK", a series of albums housing Grime music available on Spotify. From these volumes I noted the 179 individual artists that performed thereon. Fourth, I used the book "This Is Grime" (Collins & Rose 2016) and wrote down the 63 artist names that are in it. Fifth, I looked at volumes 3-8 of "Lord of the Mics" available on Spotify and wrote down the 70 artists represented on those albums. Lord of the Mics is a rap platform hosted by artist/producer Jammer specifically for Grime MCs. The first 2 volumes were only available as DVD, hence only 3-8 are available. Sixth and finally, I used Spotify's API and the Spotifyr package's get_genre command to scrape Spotify for grime artists. This method is limited to 50 artists. In Total, these methods yielded a total of 377 individual artists (deleting the overlapping artists gathered from each method). However, due to collaboration with non-grime artists, this sample included non-grime artists. I therefore used Spotiryr's get_artist argument which provides a list of which genres are associated with the artist's profile. I kept only those that listed Grime as an affiliated genre which left me with 122 artists.

Table 1: Data Sources

	Crew List DJ Target Book	Grime Classics	This is Grime UK	This is Grime Book	LOTM	get_genre	Full Sample	Spotify: Only Grime
N	146	46	179	63	70	50	377	122

I note that the hand coded nature of the archival sampling technique, although not new to studies on music (c.f. Crossley 2008), is imperfect and leaves room for researcher error. For example, artists in Grime may have multiple names or slightly different versions of the same name are on Spotify. Ghetto switched to Ghetts later in his career, for example. Or J-1 and J1 may be seen across sampling methods. As such, I used multiple techniques to check my coding efforts to ensure that the Grime artists included in the sample were legitimate. I carefully merged names where available removing doubles from each sampling method to arrive at the 377 full sample. Then I reduced the sample from 377 artists to the 122 Grime artists. Restricting the sample in such a way proved to filter any non-Grime artists as well as ensuring the artists were legitimate. To filter them, I used Spotifyr's get_artist command which lists the genres associated with the artist. This required that an artist has a link on Spotify. Any artists not with Grime in their list or without a Spotify link were discarded. In determining which profiles to use on Spotify, I had to exercise judgement based on pictorial evidence on profiles where available matching artists to their faces found in other sourcebooks or online and use my best judgement to ensure the songs on their profile are known Grime songs.

The final analytic sample is an unbalanced panel of 122 grime artists observed between 2001 and 2022. Pay as you go Cartel, a Garage Crew formed by Grime artist Wiley, released what was seen to be an early Grime Song called 'Know We' in 2000. The panel, therefore, begins after that date as Grime emerged from the Garage scene. The artists in the sample are considered in the networks when they make their debut on their Spotify profile. However, there are some artists who enter and exist the networks prior to their first publication because they collaborated with other active artists prior to their own first release. All active artists in any given year are counted. This means the unbalanced nature of the panel data includes artists like Roll Deep who collaborate in 2002, then do not publish their own work until 2009. Roll Deep is counted in 2002 and then again from 2009 onwards.

Since the aim of the study is to explore collaboration and to use Grime as a case, I maintain that the sampling methods used provide a representative sample of artists on Spotify. In fact, the genre is so small, that the statistics from this sample are likely closer to population statistics. Of the Grime artists on Spotify, I am confident that this sample represents most of them because of the triangulation of multiple sampling methods including the archival approach using the Grime Library (Boakye 2018; Collins & Olivia 2016; Hancox 2019; Lester 2010; Sinclair 2019; Stormzy 2018; Target 2019; Tempah 2011; Wiley 2017). The 122 artists in the final sample are legitimate Grime artists who have profiles on Spotify. Since the career success measures used in this dissertation come from Spotify, it was imperative that each artist's profile match with the career data collected. This sampling method blends both purposive and algorithmic sampling techniques and required a lot of in-depth knowledge of the genre and the artists to obtain a representative sample.

Career Success Data

To obtain artist-level career success data I matched artists in the sample with their Spotify profiles. Each profile has a unique identifying link that can be used to access the profile. Part of the link includes an identification number that identifies the artist and the profile associated with them. Using this identification number, I collected career success data by scraping it from songstats.com API.

Songstats.com is a third-party data repository that houses artist-level data from a collection of streaming services ranging from apple music to Spotify, Amazon music, and others, and houses historical data on the artist's career success. Since Spotify is among the oldest streaming services, the data collected on Spotify are the oldest and the broadest available on Songstats.com. I used songstats.com API through R to pull Spotify data including an artist's streams, monthly listeners, followers, popularity, playlist reach, and number of playlists they are on. These measures were tracked earliest 2015-2023 with some measures that were collected from 2017 onwards. The data were recorded at the artist level daily when available. Some artists had limited recorded data available. I transformed the variables for the uses of each chapter.

I also used the archive option available at www.officialcharts.com to ascertain whether artists charted (top 100 in UK), how highly they charted, and how many songs they had each year on the charts. These variables demonstrate success outside Spotify as a context. This enabled me to control for the possibility that success on Spotify happens because of success outside of Spotify.

Network Data

I generated edge lists of all the collaborative works artists published each year (starting in 2001, ending end of 2022) on their Spotify discography. Using the Spotify profile links taken from the sampling list, I searched through every artist's discography on their Spotify profile and hand coded who they collaborated with each year. This process resulted in a list of artists' collaborators. From this I generated two sets of yearly edge lists, one that included all collaborations per year and another that included only those in the sample per year. Edge lists, traditionally, are organised into "From" and "To" columns. For this project, I label these as host profile and featuring artist. The direction of the collaborations is structured so that a collaboration from a featured artist is incident upon the owner of the profile. In other words, the featuring artist sends a collaboration to the owner of the profile. If an artist worked with the same feature multiple times within a year, I generated a weight for each collaboration.

Artist Data

Beyond the artist-level career success or collaboration, I also collected data on each artist. I gathered information whether the artist is a MC or DJ, and if they are male or female from several books in the grime library (David 2019), namely Hancox (2019), Wretch (Sinclair 2019), DJ Target (Target 2019), Wiley (Wiley 2017), Stormzy (Stormzy 2018), Boakye (Boakye 2018), Dizzee Rascal (Lester 2010), Tinie Tempah (Tempah 2011), and Collins & Olivia (2016).

From the Spotifyr get_artist command I also recorded how many genres the artist is associated with and whether they span multiple genres. From their Spotify discography I also noted their productivity by recording the number of songs and albums they released each year since their debut on Spotify. Due to the longitudinal nature of the data, only the time-variant variables were usable in the analysis (discussed below).

Methods

Each empirical chapter uses different methods to explore the collaboration between Grime artists and the career success they experience. In broad strokes, the methods used in the dissertation primarily focus on network and statistical methods. Each study details the methods used for that study at length. The present section, however, introduces what methods are used and justifies why they are appropriate for studying the case.

Network methods.

There are two types of networks methods that I use. The first focuses on the networks of grime artists and the second focuses on the individual artists in the networks. The dissertation frames

Grime as a network. As such it uses network measures to map the topology of relationships among Grime artists. In Chapter 3, I map the changes of network order, size, density, and the changes of community modularity within the network to describe the evolution of the Grime network. Such measures of network topology appropriately describe the structure of relationships in terms of how many people are involved in the genre, how many connections there are between participants, and how densely grouped together or clustered the artists are from one another.

The second set of network measures focuses specifically on the positions of artists within the Grime networks. Chapter 4 uses measures of centrality operationalized in terms of an artist's prominence, power, and the halo effect of connecting with influential others. Relatedly, Chapter 5 utilizes the types of connections between artists and theorizes that the type of collaboration an artist has (on their profile vs. on another's) influences their career success differently. Finally, Chapter 6 generates a unique node-level characteristic of group reciprocity status by creating a ratio of in- and outdegree connections between an individual node and the whole group.

Statistical Methods.

The longitudinal nature of the data meant that the most appropriate approach was to use fixed effects models when predicting relationships between variables. This meant selecting only time-varying variables to include in the models. Controlling for the unobserved heterogeneity in models meant that all time invariant variables were not included in the model (e.g. my measure for artist role and gender). Across the three studies I use fixed effects models with robust standard errors to maximise the confidence in the robustness of the effects. Where appropriate, I also control for year-effects to ensure the observed relationships are not due to natural variation across time.

One major concern for modelling the statistical methods in this dissertation was the small sample size. I took two steps to ensure I could appropriately deal with this concern. First, I constructed parsimonious models. To truly isolate the effects of key independent variables on outcomes, I selectively built models with few appropriate time-varying controls. Due to the small cell sizes, parsimonious models maximise the degrees of freedom which directly influences the statistical power of the models. Researchers with larger samples may saturate models to explore the mediation or explanatory effects of covariation, however, the focus of this research was to build simple parsimonious models to test empirical questions about a few principles/variables. I also report statistical significance beyond canonically accepted alpha ranges (0.001 – 0.01). I include findings that with p values < .1. As such, interpretations, and discussion on generalizability to larger groups is subjective. Further, the robustness of the effects along with the possibility that the observed effects are due to chance are also debatable. However, given the small sample size used in the models, it is appropriate to report findings and consider significance beyond 95% confidence due to the small degrees of freedom from even these sparse models.

CHAPTER 4: EMBEDDED IN GRIMY NETWORKS: NETWORK POSIITON AND THE CONCEPT OF EMBEDDEDNESS IN GRIME MUSIC

Abstract

This chapter adopts the network position approach to studying the benefits of collaboration. Specifically, it tests three common measures of network centrality. First. whether having a high degree of prominence in collaborative networks boosts success. Second, whether betweenness and control over the collaborative network is rewarded by listeners. Third, whether there is a halo effect when artists connect with prominent others (eigen centrality). It also tests the paradox of embeddedness as it relates to artists in music where the success of highly connected artists is diminished. The results suggest that prominence and power drive benefits of embeddedness. There is limited evidence to suggest that the halo effect operates in Grime. Results also show an inverted U-shape relationship between the three forms of network embeddedness and multiple career measures. This suggests a dilution by over affiliation operates among collaborative networks in Grime.

Introduction

Collaborating in workplaces is associated with myriad benefits on one's career success. Across multiple industries scholars of collaboration demonstrate that working with another streamlines the process of work and increases the quality of the product generated (Alsharo 2017; Cui et al. 2021; Leahey 2016). At the same time, working in teams renders other benefits related to the network of relations that is constructed as workers collaborate. Collaboration can generate positive affiliations among workmates that helps people stay accountable to their work and boost performance as a community (Burt et al. 2022; El Mezouar et al. 2019; Mora-Cantallops & Scillia 2018; Yakubovich & Berg 2019). In music recent scholarship has discovered that collaboration benefits artists through the quality and success of the song produced. For example, collaborated songs are played more on the radio (Deshmane and Martínez-de-Albéniz 2023). However, how the effects of network position and embeddedness on career success in music is largely understudied.

The construction of the music industry offers an interesting setting in which to study the network effects of collaboration because of its competitive nature. Mark (1998; 2003) demonstrates that the music industry is structured into niches of listeners and artists. Musicians compete with other musicians for music listeners. Thus, when artists collaborate, they are effectively collaborating with a competitor. Studying collaborations in music from a network perspective can offer insight into how the embeddedness of artists in a network of competitor peers either positively or negatively impacts their success. It is possible that highly embedded artists experience more success because they are perceived by listeners to be prominent or powerful within their genre. Meanwhile, it is also possible that collaborating with other artists could diminish an artist's success due to the competitive nature of the music industry.

The current study uses data scraped from Spotify repository songstat.com API and data collected from the Spotify profiles of 122 Grime artists to explore the effects of network centrality on the career success of musicians. First, the study examines the effects of degree centrality and the prominence of artists in the genre. Second, the effects of betweenness centrality as a measure of the control an artist has among the collaboration network and how it influences their success. Third, the effects of eigen centrality and whether being associated to influential others in the network boosts an artist's success. Finally, the study explores the possible paradox of embeddedness (see Uzzi 1997) where the success of artists who are too connected with collaborators diminishes.

Background Literature

Network Structure and the Concept of Embeddedness

The concept of embeddedness emerged from economic sociology and has been adopted by many social network scholars interested in the role of structural position of people (or other entities) related to others. Polanyi's (2001) original conceptualization of embeddedness was used to explain the way that capitalism disembedded economic behaviours from social institutions. Granovetter's (2017) work on society and the economy adopted this framework but maintained that people and their actions are embedded within a framework of other people (a network) and the context wherein they operate. This vein of thought has sparked a rich literature on embeddedness in networks and the effects of people's structural position across various outcomes.

One of the most direct methods to capture a person's or entity's embeddedness within a network is to measure how central they related to others in the group. Centrality, although defined in many ways, basically measures how important or influential a node is within a given network. Important nodes may be those that hold a network together and are thus structurally embedded through their integral role within the group (Neal 2014; Olson & Neal 2015). Meanwhile, influential nodes are those who are deeply embedded in the network though a high amount of connectivity, or a strategically manicured position of connectivity (e.g. filling a structural hole, see Burt 1995). Key assumptions among network scholars interested in centrality are that information or resources flow among people and that specific positions within a network demonstrate more or less control over those resources. The control over resources, or the notoriety of an individual person (or node) within a network is often conceived in terms of their power over outcomes (e.g., Krackhardt 1992), accessing new or nonredundant information (Burt 1995; Granovetter 1973), or control over the flow/ongoings of a given group (Borgatti 2005).

Critiques of the concept of embeddedness and structural positions in networks argue that the scholarship on embeddedness has become too structural. Kripner and Alvarez (2007) argue that the concept of economic embeddedness is overused and often inappropriately applied. They maintain that the concept of economic embeddedness is not so easily reduced to a numeric figure of connectivity or disconnectedness. Despite this, scholars have leveraged the concept to explore the role of social connectedness in determining many life outcomes.

Ongoing research among scholars of health leverage social networks, embeddedness, and centrality to track the spread of contagions (Bearman et al. 2004; Christakis & fowler 2007). Scholars of culture demonstrate how cultural trends are diffused across networks (Lizardo 2014) and that networks are shaped because of culture (Feld 1981). Furthermore, studies on work and employment demonstrate the necessity for social networks in getting a job through the application of social capital (Lin 1999; 2001; Lin & Ao 2008; Pedulla & pager 2019), accessing nonredundant information to hear of job openings (Granovetter 1973; Kim & Fernandez 2017), and to get promoted (Podolny & Barron 1997). The current study focuses on collaborative networks and the role of embeddedness on career success.

Collaboration, Embeddedness, and Career Success

There are two primary mechanisms through which collaboration is beneficial to career outcomes. First is the augmentation of the process and product. Working with others can expedite the process and boost the quality of the product because collaboration facilitates an exchange of resources between people that augments the process and the success of the product. In general, project success is strongly determined by the successful management of collaborative teams (see

Ali et al. 2021). As experts collaborate, they share knowledge with one another that proves (Alsharo 2017) which helps streamline the process. The collective knowledge of multiple experts on one project often helps both the productivity of the team and the quality of the project. For example, Cui and colleagues (2021) studied academic physicists and found that collaborating on research projects lead to more productivity for individual scholars, higher impact of their work, and even longer careers, especially when they collaborate with other prestigious scholars. Moody's (2004) work on collaborative academics found that scholars tend to collaborate on projects where the division of labour is easier to outline. For example, Moody finds that quantitative research is often more collaborative than qualitative, suggesting that professionals tend to collaborate on projects where they can clearly define their role on that project. Such clear assignments and articulated expectations avoid conflict in teams (Patel et al. 2021). Evidence for the augmentation of collaboration on process and product has been studied in business settings, (Burt et al. 2022), among academics (Leahey 2016), e-sports professionals (Mora-Cantallops & Sicilia 2018), and coding professionals (El Mezouar et al. 2019; Zoller 2020),

The second mechanism through which collaboration operates is a community or network effect that collaborative ties facilitate. Working within a network of other people provides a multitude of benefits to individuals within the group, some related to the ties that exist between the actors themselves (endogenous to the network) and others relate to resources gained through network connections (rewards through the network). Several studies show that working with others generates a sense of community between collaborators by building strong affinity for one another (Yakubovich & Burg 2019) and accountability to the group (Burt et al. 2022). Uzzi's (1997) work on interorganizational collaboration shows that some of the resources and rewards are the access to fine-grained information, trust, and joint problem-solving. Uzzi finds that embedded relations of collaboration that are built on positive interactions, reciprocal exchanges, and a clear division of labour provide the actors in the collaborative relations access to hard-to-reach resources that they would not have had access to otherwise. These studies demonstrate that the ties, and structure of people's networks influence the availability and flow of resources in the group which impacts performance.

One of the largest costs for collaboration is the paradox of embeddedness and the nonlinear effects collaboration can have on career outcomes. While embedded collaborative relations are helpful, being overly embedded in collaborative networks can diminish returns and opportunity costs. Uzzi (1997) also finds that, overtime, cohesive teams end up struggling from feuding, lack new and novel information/opportunities, and can ultimately fail to operate effectively. Collaborating in teams can also be very challenging as individuals and organizations bring together different opinions and approaches to certain projects. Thus, there can be "too much of a good thing" and too much collaboration can negatively impact individual and team performance.

Success in Music, Augmentation vs. Community Embeddedness

"*Gotta Keep it movin, Fans are gonna be fans out here – always pickin and choosin. Most people start gravitating to the artist they see who's in*" (Wiley 'Keep it Moving').

Multiple studies document the salience of collaboration on the career success of artists in music but very few consider the role of centrality and embeddedness. The current paper explores the network embeddedness perspective on the career success of musicians. Specifically, that network embeddedness and the position one holds within a network drives their success through the influence and importance that artists have over the genre.

Why Music? Collaboration in music is interesting because the music industry is competitive since musicians compete for music listeners. Musicians are a prime example of workers whose success relies on their dominance over others in their field. The above quote from Wiley, a UK-Grime artist, demonstrates that musicians must keep attracting listeners and that listeners are discerning about what music they consume and which artists they follow. This exemplifies the theory of creative ecologies. Building on the Field theory of Bourdieu (Swartz 1998), and Becker's (2008) art world, modern sociologists argue that the industries associated with art, and the organization of the arts are akin to "creative ecologies" wherein artists gather into small relevant groups and these groups compete with others for the consumption of their products (c.f. Roberts & Strandvad 2022).

The construction of genres follows a pattern of creative ecologies as a network of artists emerges through collaborating with other genre artists. Building on the concept of homophily and propinquity (McPherson 1983, Simmel 1955), Mark's (1997; 2003) work demonstrates that music listeners tend to group with similar others that listen to the same genre. Further, that the structure of the music industry follows a competitive, ecological pattern with individuals (artists) competing over pools of resources (listeners). Artists are bound to the conventionalities of their genre (Lena 2014), and listeners reinforce those boundaries through their sensitive tolerance to genre unconventionalities (Silver et al. 2022). Thus, collaborations that occur in music constitute collaborating with competitors. This creates an interesting case to discover whether one's ability to position themselves as central to the genre determines their success.

Collaboration Augments the Success of Songs. Much of what is known about collaboration in music follows the augmentation mechanism. Beginning with Peterson's (1999) discourse on country music, scholars demonstrate that musician's band together into niches, or genres of music and work with each other by conforming to musical conventionalities associated with their genre (see also Lena 2014). The conventionalities of genres are rigid and music listeners are punitive to those who transgress the conventionalities associated with the genre (see Silver et al. 2022). Musicians also work with others in their genre through their music to tell a cohesive story associated with the culture of their genre (Gibson 2014) and weave together through referencing one another in their music (Hodson 2016).

The logic behind the argument for collaboration in music is that it augments the resources rewarded to collaborating artists. Some genres are more collaborative than others (South et al. 2020) but, in general, collaboration positively impacts an artist's success. Like collaboration in other industries, artists bring together skills and resources to create a song that is better because they both worked on it. Further, each artist has their own listening (fans). Thus, a song that is a collaboration between two or more artists is likely listened to by the fans of each collaborating artists. This exemplifies the augmentation of collaboration in music. For example, Deshmane and Martinez-de-Albeniz (2023) find some evidence to suggest that this is the case. They use radio-play data of artists from 25 European countries to examine whether collaborative songs receive more plays on the radio than solo songs. They also test various ways that these effects might occur differently for elite vs. non-elite artists, and even be moderated by their structural position as being more central to the network of collaborators. They find that collaborated songs receive more plays than solo songs, that non-elite artists receive a boost in all their song listens when their collaborated songs are played on radio, and that collaborating with someone who has higher social capital increases their plays. Thus, the augmentation mechanism has been tried and tested in music. The current study builds from the degree centrality finding in the Deshmane and

Martinez-de-Albeniz (2023) study and explores several network mechanisms of collaboration in music.

Community Embeddedness and Network Position in Music. Alternative to the augmentation of song success, the career success of artists may be driven by their position within their network. This mechanism goes beyond the product of the collaboration and shifts towards a more symbolic approach to the capital (see Emirbayer & Johnson 2008) held by artists – their reputation, prominence, and power. This study focuses on the network position element of community embeddedness as a driver of career success in a genre. Specifically, centrality among a network of musicians may generate career success in two main ways, the prominence, power, and the halo effect that comes from someone's network position. Prominence alludes to the popularity within the genre itself rather than the listeners. In other words, those who are in a prominent network position are popular artists for others to work with. Power, on the other hand, pertains to one's influence over the genre and the control that they wield over which artists have access to others. The halo effect, however, alludes to the spillover of success that may occur when an artist collaborates with an influential other. Like the studies on embeddedness across several other industries (see Krackhardt 1992; Borgatti 2005; Uzzi 1997), how central an artist is to the genre and how much control they exert over the genre may drive their success. This section builds a theoretical framework for why prominence, power, and the halo effect may be associated with greater career success.

Prominence. The degree of affiliation can be a measure of one's prominence in a genre. Affiliating with multiple others of the same genre in music clearly presents a picture of an artist within a given genre. In other words, by working with multiple others of the same genre, an artist embeds themselves within that group becoming clearly affiliated with that genre. The degree to which an artist is connected to others in their group may signify their prestige and importance within the group. Several studies on centrality hypothesise that the number of affiliations that someone has within their group marks their significance to the group (Manuel Clemente et al. 2015; Maharani et al. 2014; Zhang & Luo 2017). Deshmane and Martinez-de-Albeniz (2023) use degree centrality of artists as a measure of social capital. Although commonly used this way, I maintain that the degree centrality of an artists in a collaborative network does not only signify their popularity among the collaboration network (internally), but also their significance to the genre to the listeners (externally). Therefore, within music, collaborating with multiple artists may boost an artist’s success because listeners view them as more prestigious and central to the genre. In other words, an artist who positions themselves at the centre of a genre by collaborating with many others may be perceived by listeners as a highly prominent figure within the genre and therefore one worthy of their patronage.

Hypothesis 1: More prominent artists are more successful than less prominent artists.

Power. Controlling the flow of resources within a network is perceived as being highly valuable and powerful within a genre. Through collaboration artists control the stories associated with their genre (Gibson 2014) and who they chose to venerate (Hodson 2016). Similarly, controlling the affiliation of collaborations that occur in a genre may position an artist as a powerful figure. Specifically, being central to a network in such a way as to broker professional connections to other artists in the genre exerts control over who works with whom in the genre. Standing between artists and exerting some level of control over the collaborative ties that people have in the genre demonstrates one’s influence over the ongoings of the group (see Faris & Felmlee 2011). An artist with high levels of betweenness centrality exerts control over the flow of the network and may connect multiple subgroups of the genre. Such an artist fills an important role within the network because without them the artists in the genre may not be as connected. This may drive an artist's success because they exert strong influence over the content and nature of the genre. Listeners may be drawn to artists who exert influence over the genre they are interested in and thus, highly influential artists may be more popular than peripheral artists.

Hypothesis 2: More powerful artists are more successful than less powerful artists.

Halo. Finally, having connections with influential others may generate a halo effect around a given artist. The logic of the halo effect comes from Thorndike's (1936) work on people's estimation of others. People hold others in higher esteem if they can associate them with good morals or good others. In a network of musicians, being connected to central and influential others may enable artists to bask in the 'halo' of another. In other words, affiliation with a highly influential artist may boost listener's opinion of you. For example, if an artist who is central to the genre works with another artist, the featuring artist gains exposure to the benefits of centrality that comes from the popular artist (see Maharani & Adiwijaya 2014). Working with highly central or influential artists, therefore, likely boosts the success of others.

Hypothesis 3: Artists connected to influential others experience more success than those not connected to influential others.

Paradox of Embeddedness. There is a caveat to the embeddedness hypothesis that draws from the paradox of embeddedness. Following the logic of Uzzi's (1997) study on overly embedded corporate networks, being highly connected to others in a genre may diminish one's performance because it dilutes an artist's identity. Since music listeners are punitive of artists that blend conventionalities of too many genres and deem them ambiguous (Silver et al. 2022), affiliating with too many other artists may be detrimental to an one's success. Instead of diluting the genre's conventionalities and characteristics of music, there is the possibility of a dilution of one’s identity by over affiliation. This is where an artist may collaborate with so many other artists that they lose their own identity. Like the ambiguity that comes from blending too many unconventionalities in their music, artists may lose listeners because they are no longer identifiable. Thus, not only does diluting the conventions of the genre decrease an artist’s success (Silver et al. 2022) but diluting one’s own identity by working with too many other artists may also diminish one’s success.

Hypothesis 4: Being overly embedded through collaboration diminishes an artist’s success.

Current Study

Data and Methods

This study uses both the career success data paired with the collaboration network data. The collaboration data and career success data overlap from 2015-2022. The collaboration data used in this study includes all collaborations listed on an artist’s Spotify profile. As such, the networks from each year have artists not included in the sample of 122 certified Grime artists (see chapter 3). Some of the performance statistics (e.g. popularity) were not measured until 2018 and not every artist had valid information for every observation period and each measure. Thus, the sample across models run in the current study change depending on the availability of observations for the dependent variable. I understand that this does not allow for comparison across models. However, the paper does not mean to compare between different career success indicators but career success in general. Therefore, to maximise the statistical power with a small sample size, I maximise the number of available observations wherever possible. For example, predicting popularity will include fewer observations because it wasn’t measured until 2018 compared to streams which was collected in 2015.See Table 1 for the availability of each variable.

Dependent Variables

The focal dependent variable is career success. There are many ways to conceive career success for musicians, however the present study focuses on metrics taken from the streaming service Spotify. Spotify, like many other such streaming platforms, has replaced CD sales as a primary method for success for musicians. Success, therefore, is operationalized by artist popularity, content engagement (streams), returning listeners, and listener loyalty (followers). Some of these variables relate directly to money that artists get (i.e. being paid for each stream), while others have to do with their success garnering a following and building popularity. The focus of the study is less on parsing out the differences between types of career success, but rather on the effects of network embeddedness on career success in general. Thus, it suffices to measure many outcomes and talk of career success in general terms for the sake of the present study.

All dependent variables were scraped from songstats.com API and most were collected daily from 2015 till 2023. However, since the collaboration information has 1 observation per year per active artist, I generated yearly representations of each measure (see below). This left one career success observation per year for each artist who has collaborations that year. Further, since this sample was aimed at collecting a representative sample of Grime musicians it includes very successful artists and unsuccessful artists. Therefore, the distribution of many variables of interest were greatly affected by the extreme cases in the data. Therefore, I elected to take the natural log of the variable.

Artist Popularity. Spotify measures popularity on a scale from 0 – 100 where the higher score reflects more popularity. An artist’s popularity is affected by the total streams they have, the recency and frequency at which an artist's song is played (Alexis 2022). I created a variable to indicate the maximum popularity that an artist achieved in a year.

Content Engagement. Songstats.com collected a daily count of streams that an artist had every day. Streams are when listeners listen to an artist's songs. From this I created a variable counting the streams each day for a year. This variable is logged to account for its severe skewness.

Return Listeners. Return listeners make a big impact on an artist's success because they impact an artist's popularity and stream count over time. I created a variable indicating an artist's total monthly listers in a year. This variable was logged to account for its skewness.

Listener Engagement. Beyond just listening to an artist's music, artists can also gather a fanbase or a following. These are folk who follow or subscribe to an artist and are updated of the artist's new releases. This is a measure of the total number of followers that an artist has in a year – logged to account for skewness.

Independent Variables.

Network Position and Embeddedness: To test the embeddedness hypothesis I leverage three commonly used measures of network centrality. First degree centrality to measure the level of prominence of an artist in a genre. This is a continuous variable that measures the total connections that an artist had in given year. It is derived from each year the network. Second, betweenness centrality to capture an artist's power and influence over the collaborative network. This is a measure of the number of times an artist fills the gap for other artists along the geodesic path across the network. In other words, how many times they are part of the shortest possible path across the network. This captures the extent to which the artist exerts control over relationships in the genre by playing a brokerage role. While the other measures are taken from the directed networks, the betweenness is undirected. The logic behind this is that the direction of the collaboration does not influence the connection between artists nor the artist's control over the flow of connections in the network. I divided the artists' undirected betweenness by 200 to account for the skewness and extreme range. Third, eigenvector centrality captures the influence of a node over the network and quantifies the extent to which nodes are connected to influential others. The eigenvectors used in this study are directed since the direction of the collaboration indicates whether an artist appears on the profile of another of has another artist on their profile. Therefore, the eigenvectors capture whether artists are connected to artists whose profile has many other artists on them. Connections with such highly connected and influential actors in the network furnish a node with a higher eigenvector value.

Control Variables

Productivity. Artists may get more streams because they simply produce more music. I control for the number of songs artists produced during a year.

Opportunity. Spotify places artists' music into playlists which, by use of algorithms are circulated to listeners which directly influences the possibility of listeners streaming and engaging with the content. Thus, I control for the total reach of the playlist that featured these artists.

Success: An artist may experience a boost in Spotify engagement if they are experiencing success elsewhere, like in the charts. For this study I control for the number of songs that, and artist has in the UK official Charts (top 100).

Analytic Strategy

The first step in the analysis describes the sample and the network of collaborator. Table 2 presents descriptive statistics of each variable included throughout the models. Figure 9 presents a network map that shows the collaborative connections and structure of relations between those in the sample and those with whom they collaborated. The map on the left presents collaborations in 2015 (the first year of analysis) and on the right is 2022 (the last year of analysis). Figures 10 and 11 have three panels showing the same network maps from Figure 2 but present the centrality of each artist. Figure 10 presents 2015 and Figure 11 2022. From left to right on both figures the first map shows the degree centrality of the artists (the bigger the node, the higher the value). The panel in the middle overlays the betweenness centrality to the node size of the network map. Finally, to the right the node size reflects the eigenvector centrality of the nodes.

The second step tests hypotheses 1-3 using fixed effects regressions models. The data represent an unbalanced panels with person observations nested in years. Models throughout Tables 2-5 represent fixed effects models controlling also for yearly variation. Furthermore, they present robust standard errors to maximise confidence in the significance of the results. Table 3 tests Hypothesis 1 and shows the effects of degree centrality (prominence) on each dependent variable. Table 4 tests hypothesis 2 testing betweenness centrality (power), and Table 5 tests hypothesis 3 testing eigen centrality (the halo effect). The third and final step of the analysis is to test the paradox of embeddedness Table 6 presents truncated models testing the nonlinearity of the paradox of prominence (top), the paradox of betweenness (middle), and the halo effect paradox (bottom). The table models show the fixed effects regressions across each dependent variable (Models 1-8) but only presents the main effects and multiplicative effects. Each model was run, like the rest of the analysis, controlling for year effects using robust standard errors. The full tables for each are available in the appendices. Figures 12 –14 present the predicted margins from the statistically significant models in Table 5 to visually portray the relationship and demonstrate what the paradox of embeddedness looks like in Grime.

Results

The mean level of popularity for Grime artists is around 49 out of 100 with a standard deviation of around 17. This suggests that there is a large amount of variance in the levels of popularity observed in this sample. The mean logged streams, monthly listeners, and followers are 13.52, 16.92, and 15.34 respectively. The ranges on these variables suggest that they remain left skewed despite being the log of the original variable. On average, artists have a degree centrality of 5.21 and the highest observed is 44. However, the betweenness centrality has a mean of 10.01 and a range between 0-157. Meanwhile the eigenvectors suggest that the average artist has an eigen centrality of 0.09 with a range between 0 and 1. The control variables suggest that the average artist has around 7.15 total songs. The mean log of the playlist reach is 18.24. Finally, on average an artist has fewer than one song or album in the UK charts.

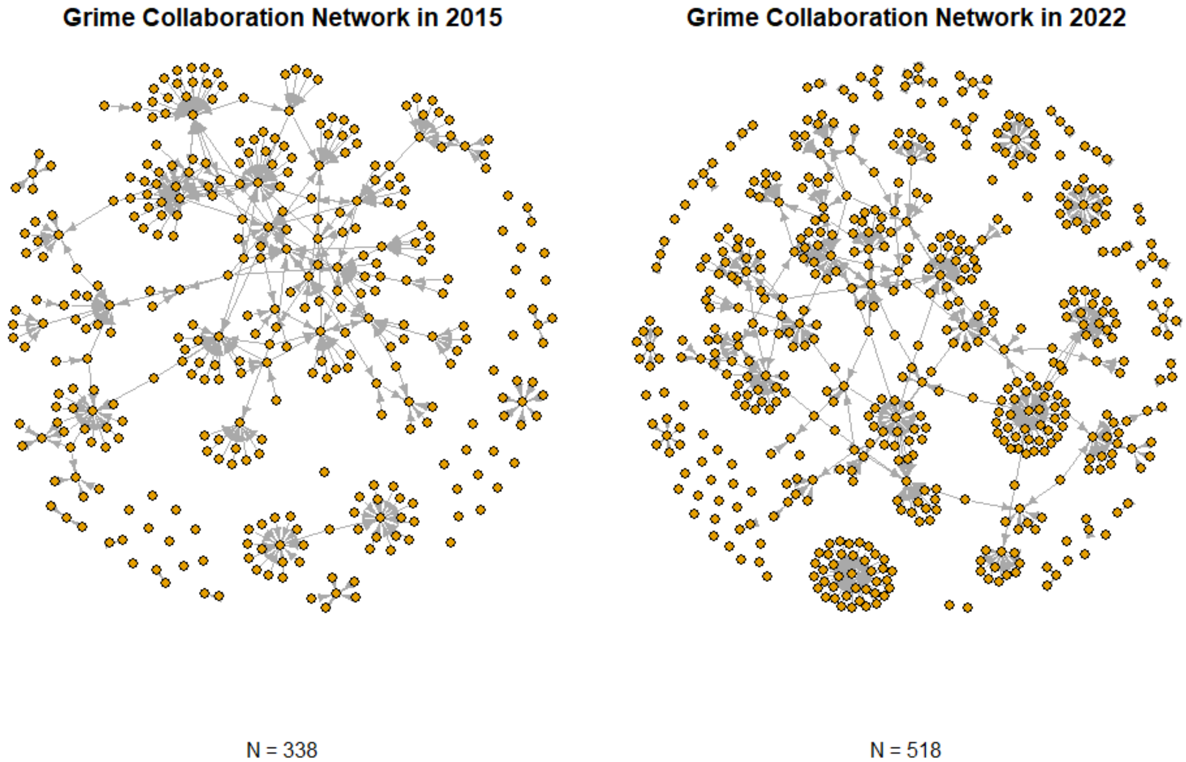
Table 2: Descriptive Statistics for Grime Artists

Variable	Range	Mean/Proportions	Standard Deviation	N (n)
Dependent Variables				
Popularity (2018-2023)	3 - 88	48.60	17.34	440 (118)
Logged Total Streams (2015-2023)	0.69 - 20.47	13.52	3.44	1073 (122)
Logged Total Monthly Listeners (2018-2023)	6.12 - 22.02	16.92	2.72	440 (118)
Logged Total Followers (2018-2023)	7.04 - 20.53	15.34	2.45	440 (118)
Independent Variables				
Degree Centrality (2015-2022)	0-44	5.21	6.61	936 (122)
Undirected Betweenness Centrality/200 (2015-2022)	0-157.85	10.01	19.97	935 (122)
Eigenvector Centrality (2015-2022)	0-1	0.09	0.18	936 (122)
Control Variables				
Songs Total (2015-2022)	0 - 96	7.15	9.60	976 (122)
Logged Playlist Reach (2015-2022)	6.86 - 24.39	18.24	3.28	876 (120)
Songs in Chart (2015-2022)	0 - 16	0.3	1.21	976 (122)

Figure 9[1] presents a side-by-side network map of the first and last years observed in this study with 2015 on the left and 2022 on the right. 2015 is characterized by a central core of artists who work together (left side of the graph). These artists appear to be connected to multiple others across chains and branches throughout the whole cluster. Meanwhile, there are pockets of clusters in the periphery of the graph. For example, on the right side of the graph there are two groups connected by a bridging artist. In general, the collaborative relationships among this group appear sparse across the whole group with a core of artists. Meanwhile, in 2022, the graph on the right, there are more artists in the whole group compared to 2015. There is still a core of artists who collaborate with each other with multiple isolated artists. The core group has pockets of densely connected artists, like 2015, with multiple chains of groups of artists. This suggests that some artists bridge multiple groups of other artists. Furthermore, there are small clusters of artists along the periphery of the visualization like 2015. In sum, both visualizations demonstrate that there is a core of more densely connected artists within the Grime community. This could be those who are within the original sample. Meanwhile, the bridging and more peripheral artists may be features from outside the sample and outside the genre which might explain the clusters and isolates along the periphery of the maps. The varied structures of the clusters of artists mean that there is likely great variation in positional centrality for these artists.

[1] The N of each network-year is larger than the sample of artists examined in the current paper. As described above, the sample includes 122 artists, but the N of the networks include all collaborations from their profile, not only with the artists in the sample. All variables in the models, however, are of the 122 Grime artists in the sample.

Figure 9: Grime Collaboration Networks 2015 and 2022



Figures 10 and 11 show a series of network maps altering the size of the vertices by their centrality scores. On the left of both figures, the vertex size depicts their directed degree centrality. The middle shows the undirected betweenness centrality, and the right shows their directed eigen centrality. The size does not reflect the raw centrality score, but an altered score to best present it on the network map (i.e., divided by 100). These visuals show that there are a handful of prominent artists who have a high degree centrality. Although not the focus of this current study, the structural position of these artists, at least from visual inspection, also appears stands out as interesting. Some have a high degree centrality within the core group of connected artists while others have high degree centrality by being connected in small communities separate from the apparent core group. The middle visual indicates that those within the core group have much higher betweenness centrality compared to those on the periphery of the network. In other words, they hold more power by bridging geodesics paths across the network. Finally, a small group of artists in both years appear to have influential connections. The maps on the right indicate that, again, only those in the core group have a high eigen centrality.

Figure 10: Network maps showing Grime collaborations during 2015.

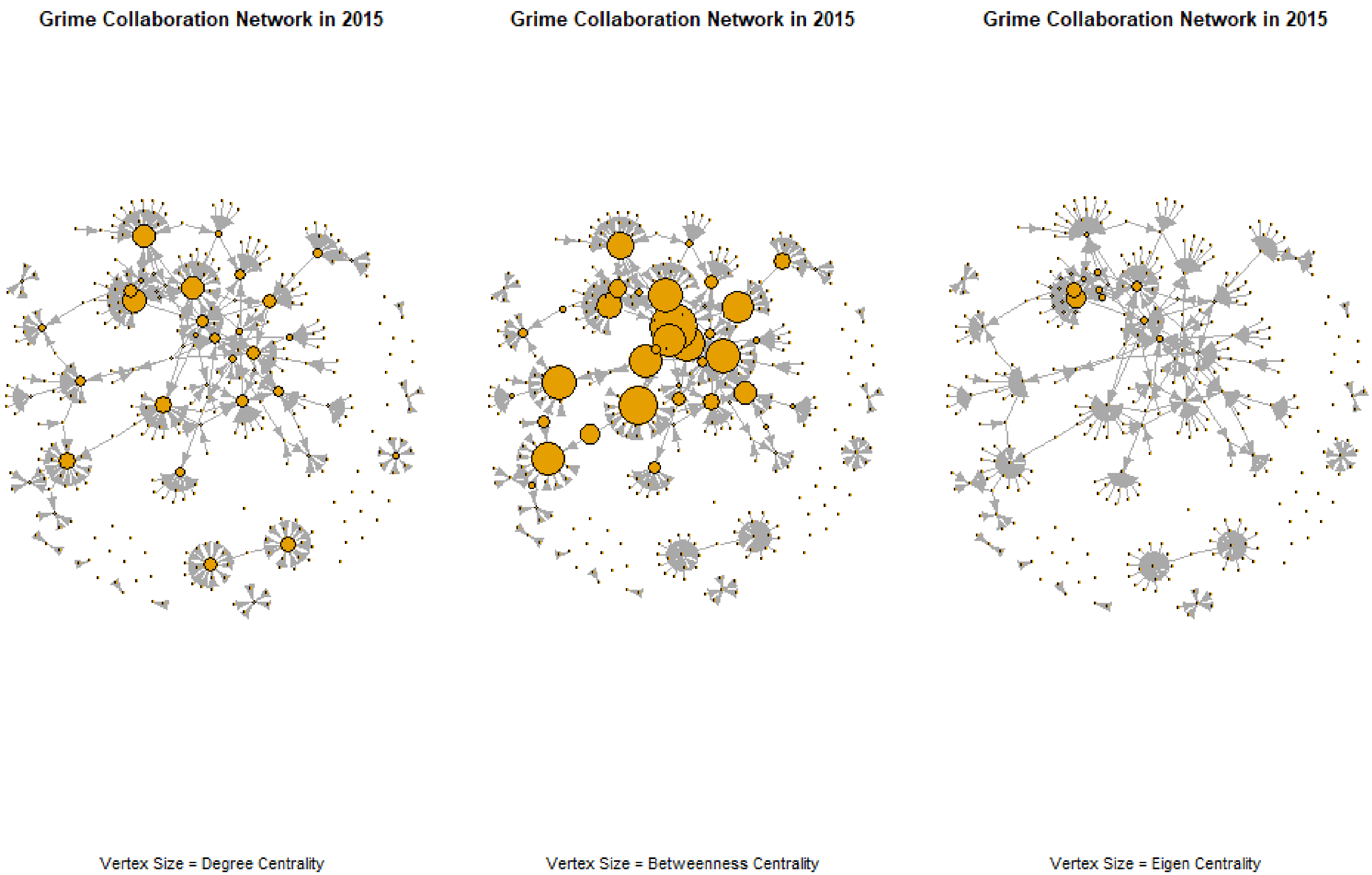
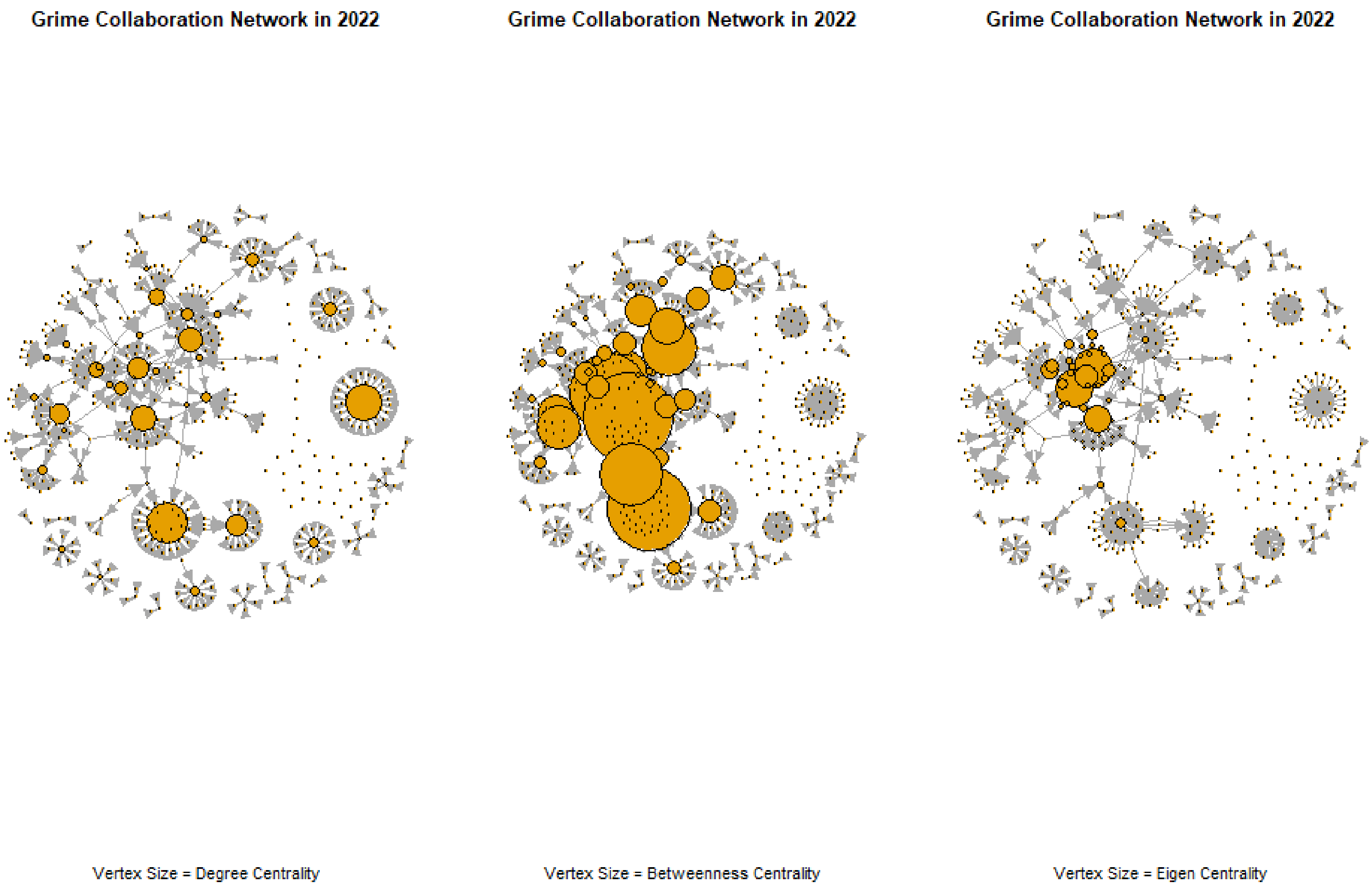


Figure 11: Network maps showing Grime collaborations during 2022.



The Degree of Prominence in Music

The results in Table 3 demonstrate that the degree to which an artist is embedded in the network through collaborative ties with others significantly impacts their career success. Since the some of the dependent variables are logged, the results for streams, monthly listeners, and followers are interpreted in their exponentiated form. Results from Models 1 and 2 show that an increase in degree centrality is associated with a 3% increase in the number of streams (epx(.03) = 1.03) that an artist receives on Spotify. This finding is significant in Model 1 when controlling for variation across years ($p < .001$), but not in Model 2. Model 2 shows that the effect of degree centrality attenuates to a 1% increase (exp(.01) = 1.01). This finding is not significant when controlling for Spotify's algorithm placing them on to playlists, the number of songs an artist makes, and the songs in the chart. This suggests that highly connected artists in the genre are placed on to more playlists, have more songs, and chart more which then explains why they have more streams.

Models 3 and 4 demonstrate that artists prominent to the genre are more popular. Model 2 shows that each additional collaborator that an artist has is associated with a 0.17 increase in their popularity ($p < .001$). Although a modest effect, this effect grows with each collaborator meaning that those with many collaborators are more popular. For example, having 10 collaborators in a year, according to this finding, is associated with nearly a 2-point increase in popularity (10*0.17). Model 4, however, demonstrates that the effect of degree centrality is attenuated ($b = 0.03$), and the statistical significance is explained when controlling for other factors. Like on streams, this suggests that artists with high degree centrality are more popular in part because they are placed on more Spotify playlists and have more songs in the charts.

Highly central artists have more returning monthly listeners. Models 5 and 6 demonstrate that an additional collaborating neighbour in the network is associated with a 4% (exp(.04) =

1.04) increase in monthly listeners ($p < .001$). When controlling for the artist's success and Spotify's playlist reach, this result remains statistically significant. Model 6 shows that each additional collaborator is associated with a 3% ($\exp(.03) = 1.03$) increase in monthly listeners ($p < .01$). These models suggest that highly prominent artists get more returning listeners.

Finally, Models 7 and 8 suggest that prominent artists Grime have more loyal listeners who follow them. Model 7 shows that an increase in degree centrality boosts an artist's following by 2% ($\exp(0.02) = 1.02$). This finding is statistically significant ($p < .001$). Even when controlling for the full model, artists the effect remains the same (Model 8, $b = 0.02$, $p < .01$). Thus, listeners of Grime music tend to follow those who are most prominent.

Together the results in Table 3 demonstrate significant support for the positive effect that comes from prominence in Grime on the career success. In Support for hypothesis 1, these results largely suggest that degree centrality is positively associated with streams, popularity, and monthly listeners. Filling a structurally central position to the genre is rewarded by the listeners of the genre. Furthermore, the effect of playlists stands out as an important mechanism describing the mediation observed in these models. This suggests that more central people get placed on Spotify playlists, and this is a primary mechanism behind them getting more streams and more popularity and a secondary mechanism behind their greater monthly listeners and followers.

Table 3: Degree Centrality Predicting Career Success

	Model 1 Streams	Model 2 Streams	Model 3 Popularity	Model 4 Popularity	Model 5 Monthly Listeners	Model 6 Monthly Listeners	Model 7 Followers	Model 8 Followers
Degree Centrality	0.03***	0.01	0.17***	0.03	0.04***	0.03**	0.02***	0.02**
	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Year	0.14***	0.01	-0.65**	-1.06***	0.08+	-0.01	0.22***	0.17***
	(0.03)	(0.03)	(0.22)	(0.17)	(0.04)	(0.03)	(0.04)	(0.03)
Songs Total		0.01+		0.03		-0.00		-0.00
		(0.01)		(0.03)		(0.01)		(0.01)
Playlist Reach		0.16***		4.09***		0.74***		0.39**
		(0.03)		(0.65)		(0.11)		(0.13)
Songs in Chart		0.06**		0.47*		-0.01		-0.03
		(0.02)		(0.23)		(0.03)		(0.03)
Constant	-264.15***	-7.25	1,353.41**	2,107.90***	-138.75+	29.39	-427.48***	-329.22***
	(51.33)	(56.66)	(452.87)	(338.23)	(78.81)	(62.77)	(75.29)	(58.78)
Observations	734	734	414	414	414	414	414	414
R-squared	0.19	0.31	0.10	0.33	0.09	0.27	0.16	0.21
Number of id	119	119	114	114	114	114	114	114

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p = 0.06 – 0.1

The Power of Betweenness in Music

Table 4 shows that power in terms of betweenness centrality is positively associated with several career outcomes on Spotify. Since I divided the betweenness measure by 200 to account for the variable's skew, associations in these models should be interpreted in terms of a 200-point increase in betweenness. Specifically, the results in Model 1 shows that an increase in betweenness centrality of 200 points is significantly associated with an artist receiving 1% more streams ($\exp(0.01) = 1.01$, Model 1 $p < .001$). This effect is lessened when controlling for the full model in Model 2 ($p < .1$). This suggests that listeners engage with and stream more those artists with more power over the genre.

Similarly, Model 3 shows a positive, statistically significant relationship between power through betweenness and artist popularity on Spotify. On average, a 200-point increase in betweenness is associated with a 0.04 increase in popularity ($p < .001$). This effect size is modest, although it does allude to the role of power in networks influencing an artist's popularity. This association, however, is not statistically significant when controlling for the full model (Model 4 $b = 0.01$, $p > .1$).

Models 5 and 6 show that an increase of betweenness centrality increases the number of returning monthly listeners that an artist has (Model 5, $p < .001$, Model 6, $p < 0.05$). When exponentiated, these coefficients equate to an average increase in listeners of 1% for a 200-point increase in betweenness.

Finally, Models 7 and 8 show a similar pattern as 5 and 6, that there is a positive association between power through betweenness centrality and the number of followers that an artist has (Model 7, $p < .001$, Model 8, $p < .01$). Again, these equate to a 1% increase in followers per 200-point increase in betweenness.

To summarize, the results in Table 4 provide some evidence for hypothesis 2, that powerful/influential artists in the collaboration network are more successful. These findings suggest that those who are structurally positioned to bridge others and control the flow of contact or resources within the collaborative community are more successful across each measure. However, these findings ought to be interpreted conservatively given that the percent increases are modest for every 200-point increase in betweenness centrality.

Table 4: Betweenness Centrality Predicting Career success.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Streams	Streams	Popularity	Popularity	Monthly Listeners	Monthly Listeners	Followers	Followers
Betweenness Centrality/200 (Undirected)	0.01***	0.00+	0.04***	0.01	0.01***	0.01*	0.01***	0.01**
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year	0.13***	0.01	-0.63**	-1.05***	0.08+	-0.01	0.22***	0.17***
	(0.03)	(0.03)	(0.23)	(0.17)	(0.04)	(0.03)	(0.04)	(0.03)
Songs Total		0.01*		0.04		0.00		-0.00
		(0.01)		(0.03)		(0.01)		(0.01)
Playlist Reach		0.16***		4.09***		0.73***		0.38**
		(0.03)		(0.66)		(0.12)		(0.13)
Songs in Chart		0.07**		0.48*		0.00		-0.02
		(0.02)		(0.23)		(0.03)		(0.03)
Constant	-252.46***	-9.20	1,327.10**	2,082.44***	-140.51+	22.51	-429.40***	-336.30***
	(52.44)	(57.44)	(463.00)	(343.70)	(80.06)	(64.51)	(75.96)	(59.67)
Observations	733	733	413	413	413	413	413	413
R-squared	0.19	0.31	0.08	0.33	0.08	0.26	0.17	0.22
Number of id	119	119	114	114	114	114	114	114

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p = 0.06 – 0.1

The Halo Effect in Music

Table 5 provides limited evidence to support the 'halo effect' hypothesis in Grime. In Model 1, a unit increase in the eigenvector centrality is associated with a 43% increase in the number of streams (exp(0.36) = 1.43) when controlling for year and unobserved fixed effects. However, this finding is not statistically significant. Further, when controlling for artists' success and productivity measures, eigenvector centrality is negatively associated with streams and is once again, nonsignificant. Therefore, these models provide no evidence to support hypothesis 3.

Meanwhile, Model 3 shows that being connected to highly influential people is associated with higher popularity. An increase in eigenvector centrality is associated with a 2.02 increase in popularity score ($p < .1$). This suggests that there is some spillover effect of popularity when artists collaborate with prominent others. When controlling for the full model this effect attenuates to 0.5 points of popularity and is no longer statistically significant.

Artists who collaborate with prominent others have more monthly listeners, but the evidence drawn from Models 5 and 6 may be due to change. Model 5 shows that an increase in eigen centrality is associated with a 42% in monthly listeners (exp(0.35) = 1.42) suggesting that collaborating with prominent others provides greater access to listeners. However, this finding is not statistically significant ($p > .1$). Likewise, the effect is partially mediated when controlling for the full model and remains nonsignificant.

Similarly, artists with prominent collaborators have more followers but the evidence from Models 7 and 8 is nonsignificant and therefore inconclusive. An increase in eigen centrality increases an artist's followers by 28% on average (exp(0.25) = 1.28). When controlling artist productivity, opportunity, and success outside of Spotify, this association attenuates to 17% (exp(0.16) = 1.17). At face value these models offer some support for hypothesis 3 that the halo effect from prominent artist's success spills over to their collaborators. However, these findings are not statistically significant.

Results from Table 4 provide limited evidence to support the assertion that the spillover or halo effect of prominent artist's success influences the success of their collaborators. While artists with prominent collaborators are more popular on average, the models yield insufficient evidence to further substantiate this hypothesis.

Table 5: Eigenvector Centrality Predicting Career Success

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Streams	Streams	Popularity	Popularity	Monthly Listeners	Monthly Listeners	Followers	Followers
Eigenvector	0.36	-0.04	2.02+	0.53	0.35	0.15	0.25	0.16
	(0.24)	(0.22)	(1.09)	(0.93)	(0.30)	(0.30)	(0.28)	(0.31)
Year	0.15***	0.01	-0.64**	-1.05***	0.08+	-0.01	0.22***	0.17***
	(0.03)	(0.03)	(0.23)	(0.17)	(0.04)	(0.03)	(0.04)	(0.03)
Songs Total		0.01**		0.04		0.01		0.00
		(0.01)		(0.03)		(0.01)		(0.01)
Playlist Reach		0.17***		4.14***		0.77***		0.41**
		(0.03)		(0.65)		(0.11)		(0.13)
Songs in Chart		0.07**		0.49*		0.01		-0.01
		(0.02)		(0.23)		(0.03)		(0.03)
Constant	-280.77***	-6.87	1,348.11**	2,095.39***	-136.92	24.58	-426.94***	-333.93***
	(52.87)	(58.51)	(469.51)	(344.64)	(84.17)	(67.39)	(78.53)	(62.82)
Observations	734	734	414	414	414	414	414	414
R-squared	0.15	0.31	0.05	0.33	0.02	0.25	0.14	0.20
Number of id	119	119	114	114	114	114	114	114

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p = 0.06 – 0.1

The Paradox of Embeddedness in Music

Evidence from Tables 3-5 provide evidence that network embeddedness in terms of the degree of prominence, the power of betweenness, and the halo effect of eigenvector centrality influences an artist's career success in Grime. What remains is to explore the possibility that these associations are nonlinear. Meaning whether the benefits of the various network positions are endless or whether there is a point at which an artist's success becomes diluted through over-embeddedness. In this case, over-affiliation. Such a pattern suggests that their identity becomes diluted through collaborating too much with others or being overshadowed by others. Table 6 presents models testing hypothesis 4 that such a paradox of network embeddedness exists in Grime music. The table covers the paradox of prominence by presenting the main effect and squared term of degree centrality first. Then the same for power through betweenness and the halo effect of eigen centrality last. The results are discussed in turn presenting also predicted margin plots from the significant models in Table 6.

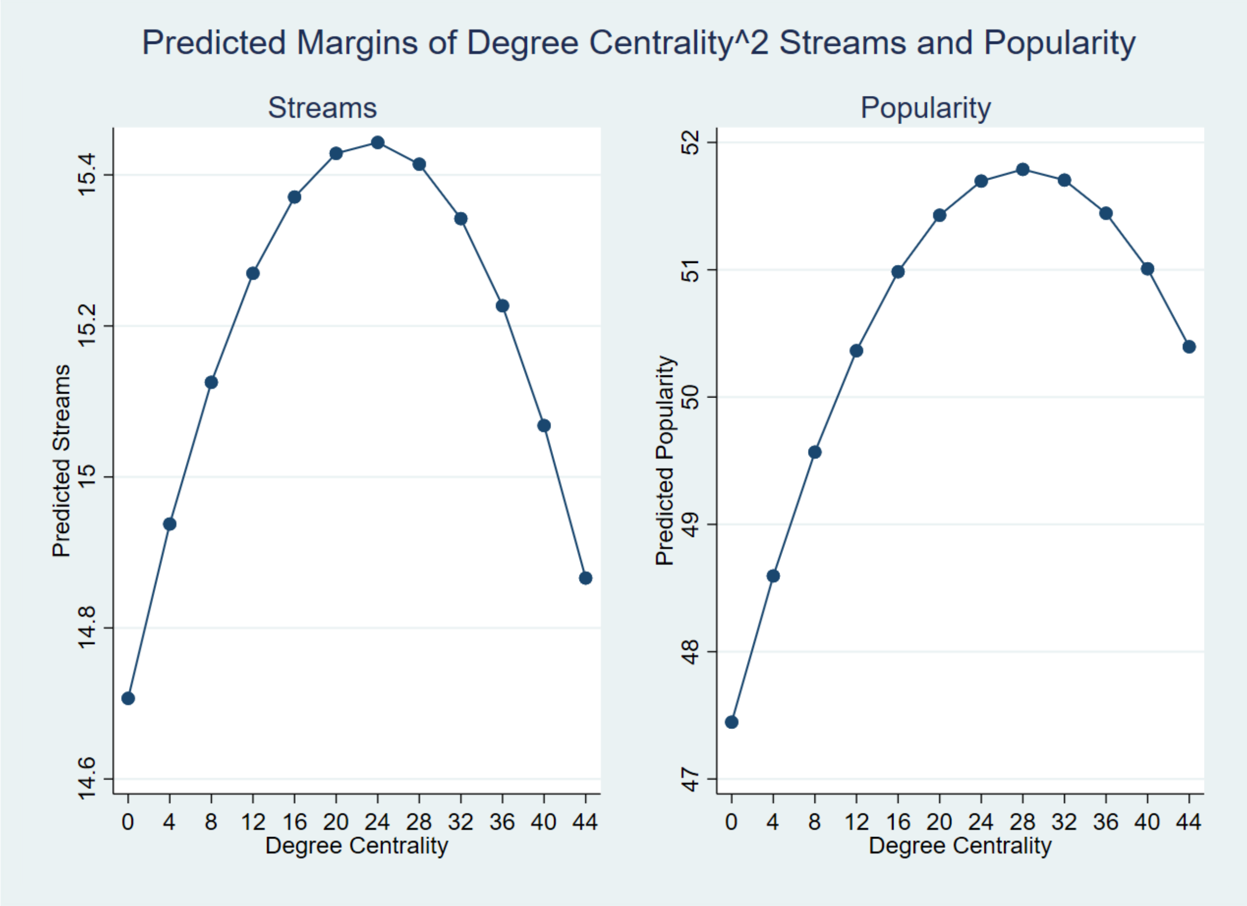
Table 6: Testing the Nonlinearity of Prominence, Power, and the Halo Effect in Grime

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Streams	Streams	Popularity	Popularity	Monthly Listeners	Monthly Listeners	Followers	Followers
Degree Centrality	0.06***	0.03+	0.31**	-0.01	0.06**	0.02	0.04*	0.03
	(0.01)	(0.02)	(0.10)	(0.08)	(0.02)	(0.02)	(0.02)	(0.02)
Degree Centrality * Degree Centrality	-0.00***	-0.00+	-0.01+	0.00	-0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-271.69***	-13.09	1,244.87**	2,141.83***	-152.75+	32.70	-436.71***	-332.51***
	(51.26)	(57.22)	(472.67)	(345.33)	(84.49)	(66.40)	(81.89)	(65.03)
R-squared	0.20	0.32	0.11	0.33	0.09	0.27	0.17	0.21
	Model 1a	Model 2a	Model 3a	Model 4a	Model 5a	Model 6a	Model 7a	Model 8a
Betweenness Centrality/ 200 (Undirected)	0.02***	0.00	0.08***	0.02	0.02***	0.01+	0.01**	0.01+
	(0.00)	(0.00)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)
Betweenness * Betweenness	-0.00***	-0.00	-0.00**	-0.00	-0.00+	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-258.83***	-12.18	1,212.96*	2,052.78***	-155.33+	17.38	-436.08***	-339.99***
	(52.42)	(58.04)	(470.25)	(347.28)	(82.77)	(67.18)	(77.62)	(61.61)
R-squared	0.20	0.32	0.10	0.33	0.09	0.27	0.17	0.22
	Model 1b	Model 2b	Model 3b	Model 4b	Model 5b	Model 6b	Model 7b	Model 8b
Eigenvector	1.42**	0.50	5.44+	1.24	0.79	0.21	0.73	0.49
	(0.44)	(0.43)	(3.19)	(2.42)	(0.75)	(0.70)	(0.67)	(0.69)
Eigenvector * Eigenvector	-1.39**	-0.69	-4.39	-0.91	-0.56	-0.08	-0.62	-0.41
	(0.47)	(0.43)	(3.23)	(2.12)	(0.82)	(0.66)	(0.73)	(0.66)
Constant	-292.28***	-13.83	1,292.97**	2,085.11***	-143.96	23.63	-434.70***	-338.62***
	(53.52)	(59.16)	(481.30)	(350.99)	(86.81)	(69.08)	(81.78)	(64.87)
R-squared	0.16	0.31	0.06	0.33	0.02	0.25	0.14	0.20
Observations	734	734	414	414	414	414	414	414
Number of id	119	119	114	114	114	114	114	114

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.06 - < 0.1

The Paradox of Prominence. Models Table 5 shows some evidence that there is a nonlinear relationship between degree centrality and the number of streams that an artist has. Model 1 presents a statistically significant direct and multiplicative effect. The direct effect is 0.06 ($p < .001$), and the multiplicative effect is negative 0.00 ($p < .001$). That they have different signs suggests that there is an inverted U-shaped relationship between degree centrality and streams. The pattern on the left side of Figure 12 demonstrates this inverted U-shape where the right side, the higher degree centrality, is negatively associated with streams, while the left side, the lower-to mid-range is positively associated with streams with a degree centrality score of 24 as the point at which there are diminishing returns. These findings suggest a ‘too much of a good thing’ phenomenon wherein additional collaborating connections positively impact streams until a point (24 connections) where the returns diminish. These findings are attenuated but remain statistically significant ($p < .1$) when controlling for the full model.

Figure 12: Predicted Margins Testing the Nonlinear Relationship of Degree Centrality Predicting Streams, and Popularity.

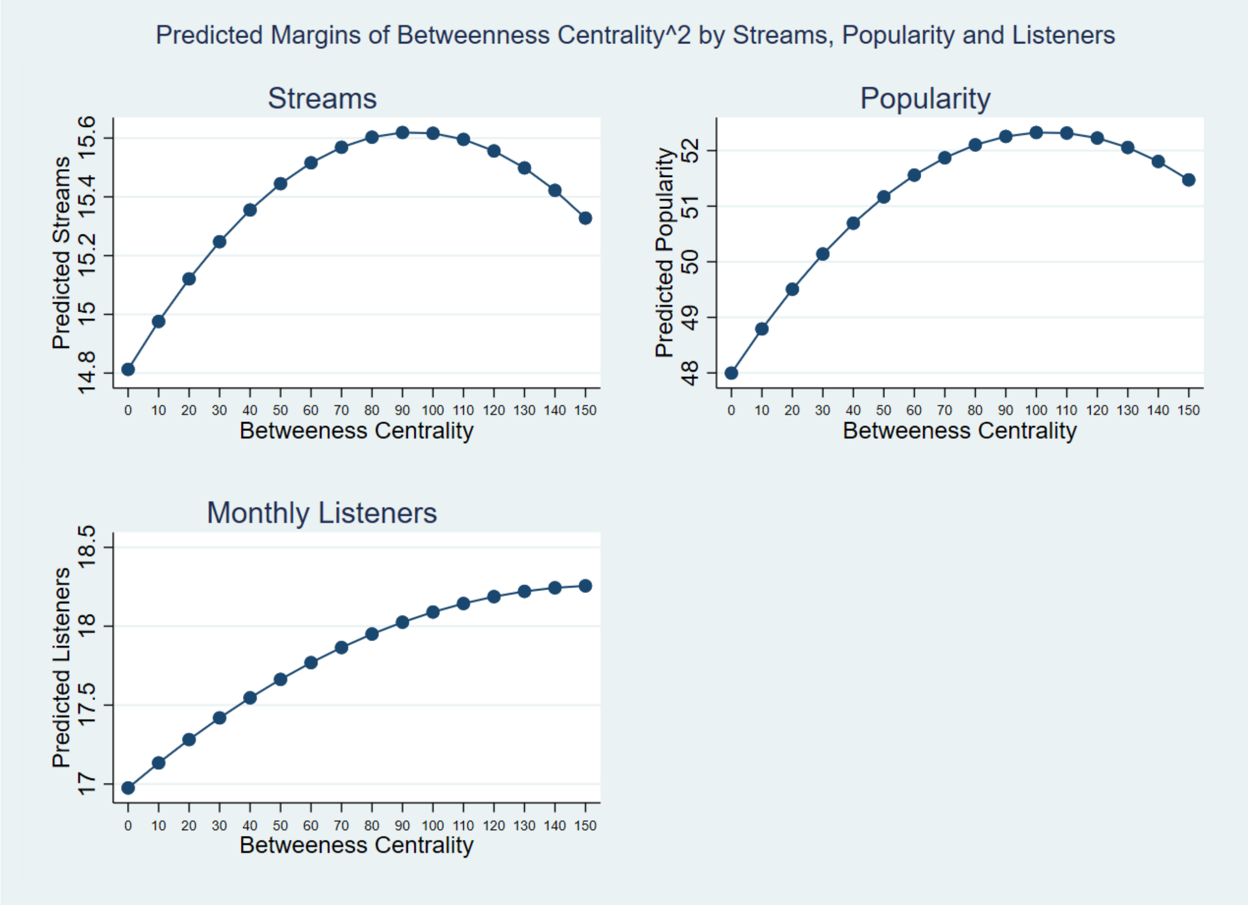


Furthermore, a similar effect emerges in Model 3 predicting popularity where the main effect of degree centrality is 0.31 ($p < .01$) and the multiplicative effect is negative 0.01 ($p < .1$). The difference in signs suggests that the higher end of degree centrality is negatively associated with popularity while the lower and mid-range is positively associated. These effects, however, are attenuated and no longer significant in the full model. The right of Figure 4 presents this relationship. The graph indicates that a degree centrality score beyond 20 the benefits begin to plateau while between 28 and 32 and additional connections negatively impact one's popularity.

Models 5-8, meanwhile indicate similar patterns of inverted U-shaped relationships between degree centrality monthly listeners and followers, however these models are not statistically significant and are therefore inconclusive.

The Paradox of Power. Models 1a through 8a repeat the same pattern of analysis as 1-8 while testing the power through betweenness centrality. Model 1a shows a positive, although modest, main effect of betweenness centrality (p < .001) and a negative multiplicative effect of betweenness centrality (p < .001). The positive main term and negative squared term, once again indicates an inverted U-shape exists between power and streams among Grime artists. The more power an artist has, the more streams they have to a point where they become overly embedded in the group and additional power dilutes their success. The top left panel of Figure 13 confirms that the benefits of betweenness centrality are nonlinear, meaning that artists who are overly embedded in the genre are not as successful.

Figure 13: Predicted Margins Testing the Nonlinear Relationship of Betweenness Centrality, Streams, Popularity, and Monthly Listeners



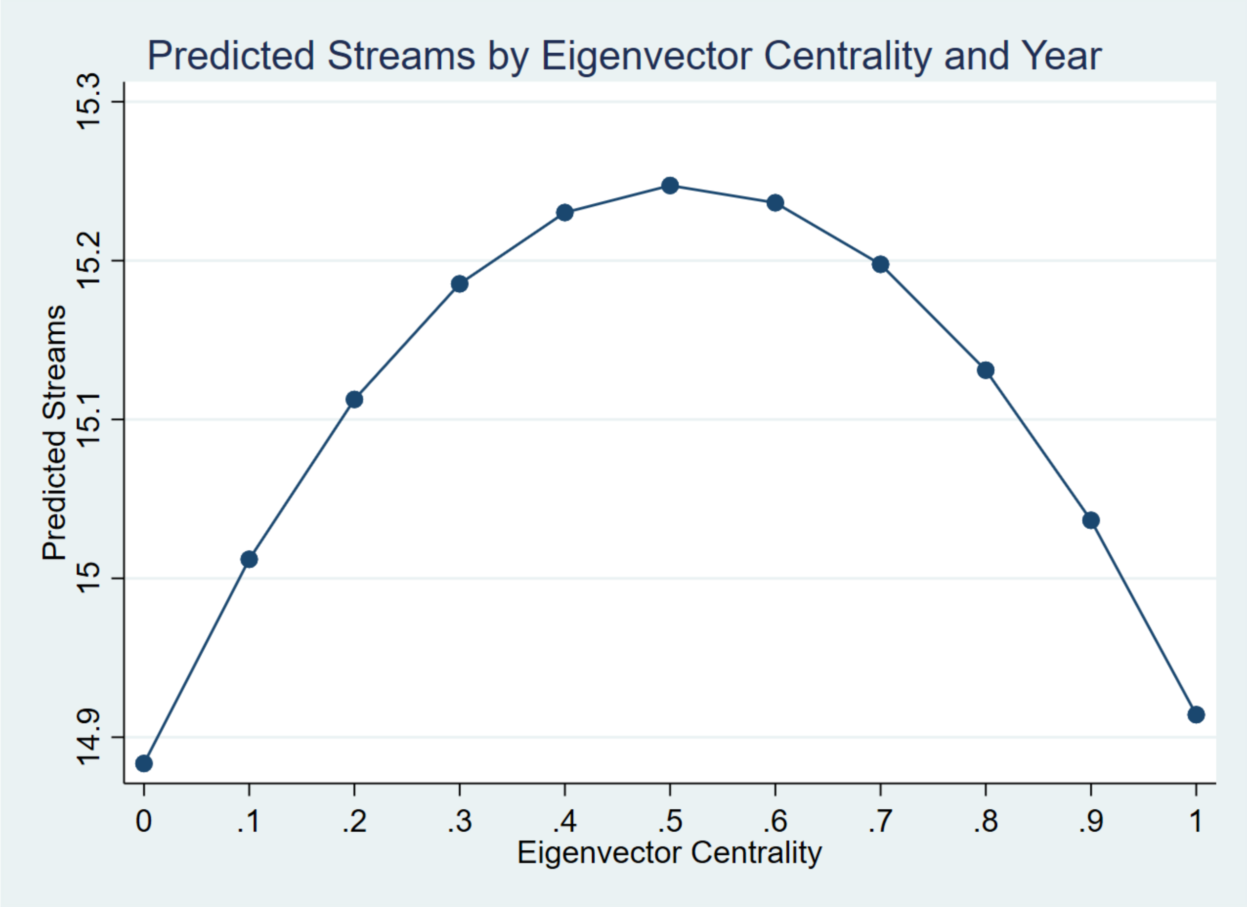
Model 3a follows the same pattern with a positive main effect ($p < .001$) and a negative multiplicative effect ($p < .01$). The upper right panel of Figure 13 demonstrates through the predicted margins that the effect of betweenness on popularity appears as an inverted U-shape. Powerful or influential artists who bridge multiple other artists within the genre tend to be more popular and the more influential they become the more popular they are. However, listeners there is a point at which centrality through bridging other artists does negatively impacts one's popularity. The right side of the predicted margins declines indicating that the 'ultra influencers' in the genre are less popular than those who exert only some influent through bridging between artists.

Finally, the paradox of power extends to monthly listeners. Model 5a of Table 5a shows the same evidence as previous models of an inverted U-shaped effect of betweenness on monthly listeners. The main effect is positive ($p < .001$), and the squared term is negative ($p < .1$) indicating those with high betweenness have experience declining monthly listeners than those with a mid-range. The lower left panel in Figure 13. However, reveals a modest curve compared to the other relationships. Despite being statistically significant, the effects of extreme betweenness centrality are negative, but the predicted margins suggest that the negative effect is minimal. The left side of the curve is positive until it reaches a point where is plateaus. Unlike the visual representations of betweenness predicting popularity and streams, the nonlinear effects of betweenness on monthly listeners appear modest at best.

The Halo Paradox. The results in Table 4 present little evidence to suggest that eigen centrality is associated with career success. The only effect with confidence through statistically significant findings was on the effects of eigen centrality on popularity. However, Table 5 shows some interesting changes to these findings suggesting that nonlinear relationships exist between the halo effect of eigen centrality and career success. Specifically, and mainly the effect of eigen centrality on streams (Model 1b) becomes significant when controlling for the squared term. In fact, the main effect shows a positive increase in streams for each increase in eigen centrality ($p < .01$). Meanwhile, the squared term shows a decrease in streams per increase in eigen centrality ($p < .01$) suggesting there is an inverted U-shape relationship like other findings in Table 5. The effect sizes suggest that the U-shape is very pronounced with a clear mid-point. In fact, Figure 14 presenting the predicted margins confirms that. Figure 14 shows a clear mid-point of around 0.5 eigenvector centrality at which the benefits of connecting with influential and prominent other artists cease and, in fact, become detrimental. Listeners engage with artists who are moderately connected to highly prominent other artists. Artists who are connected to multiple highly prominent others become overshadowed and these benefits dilute and decrease the listener engagement.

Meanwhile, the positive association of eigen centrality on popularity observed in Table 4 Model 3 remains when controlling for the squared term (Table 5 Model 3b $p < 0.1$). Although Model 3b suggests there is a nonlinear effect, in fact, the remaining models 3c-8c evince nonlinear relationships in the form of inverted U-shapes, they are all statistically nonsignificant and therefore may be due to chance.

Figure 14: Predicted Margins Testing the Nonlinear Relationship of Eigen Centrality Predicting Streams



To conclude, this final section presents evidence testing hypothesis 4 that there is a paradox of embeddedness in Grime music. The results from Table 5 and Figures 12 through 14 present clear evidence that there is an inverted U-shape relationship between prominence, power, and the halo effect on many of the career success indicators. Even among those that are statistically nonsignificant, models in Table 5 demonstrate evidence that the benefits of such network embeddedness may be nonlinear. Such evidence provides support for hypothesis 4 and demonstrates a dilution-effect of career success through over-embeddedness in collaborative networks. Akin to Uzzi's (1997) classic study on the paradox of embeddedness, these findings suggest that the dilution of over affiliation operates within Grime music.

Discussion and Conclusions

In music, the effects of embeddedness on collaborative relationships on career success has been understudied. Recent scholarship demonstrates that collaboration and an artist’s social capital augments the success (radio plays) of collaborated songs (Deshmane & Martínez-de-Albéniz 2023). The current study adds to this by adopting a theory based on position and embeddedness to leverage the logic of centrality among peers to predict the success of musicians in Grime. Specifically, operationalising artists’ degree centrality as their prominence, their betweenness centrality as their influence or power over the network, and their eigen centrality as a halo effect of connecting with influential others.

The results show that the structural positions that artists hold in a genre are associated with their success. Specifically, those with a high degree of prominence – those who are central to the genre - are more successful than peripheral artists. Further, those who have higher power through betweenness centrality are more successful than those in less strategic positions of the genre. Finally, the study offers limited evidence that having connections to influential others boosts one’s career success. In other words, there is weak evidence of the halo effect operating in Grime. However, results testing the possible paradox of embeddedness demonstrate clear evidence that an inverted U-shape relationship exists between network embeddedness in Grime and career success. Across several of the career outcomes, low levels of prominence and power were positively associated with success. However, being overly prominent or powerful in the genre was negatively associated with several career success measures. Meanwhile, there was some evidence to suggest a paradox of the halo effect whereby listeners stream artists who are connected to some other influential artists. However, they do not stream artists who are connected to many influential artists and additional connections to such artists negatively impacts the number of streams the receive.

This study contributes to the sociology of culture literatures. First, the study demonstrates that network position and the concept of embeddedness among collaborators extends across multiple fields and industries. Scholars of embeddedness and network position have studied several outcomes pertaining to the labour market (Pedulla & Pager 2019; Podolny & Barron 1997), the efficiency of interorganizational collaborations (Uzzi 1997), or the performance of teams within workplaces (Burt et al. 2022). The current study joins a burgeoning literature documenting the power of networks across multiple industries (Burt 2012; El Mezouar et al. 2019; Mora-Cantallops & Sicilia 2018; 2019) and centres the role of embeddedness in succeeding in such industries. It demonstrates that structural position within a network of peers influences not only the rewards generated internally among peers (e.g. that central people are more liked) but also that structural position influences external outcomes by external entities (in this case, listeners boosting an artist's success). This means that some of the benefits of collaboration are made available because of the collaborative centrality of individuals. Rather than generating a direct reward within the dyad (like affinity between collaborators, or the quality of their product), this study shows that collaborative centrality unlocks rewards external to the collaborators and their products.

Second, the logic of being central to a culture and the rewards that are associated with that connect well with the Bourdieusian concept of symbolic capital. Bourdieu states that those with high levels of symbolic capital are positioned in their field to exert dominance and control over the field (2005, see also Emirbayer & Johnson 2008). The current study demonstrates that those perceived as central to a field (in this case a genre) are also rewarded by the patrons of the genre through greater engagement and loyalty. In other words, collaborated songs don't just get more listeners (Deshmane & Martínez-de-Albéniz 2023), but listeners actually discern which artists are central to the genre and these findings suggest that they favour the most prominent and influential. This paper considers the degree to which an artist is central to the genre, the amount of control they exert on the flow of collaborations, and their connections to influential others. Future researchers may consider alternate advantageous structural positions that artists may hold within their field.

Third, the paradox of embeddedness (c.f. Uzzi 1997) found in the current study adds to the study of boundaries, authenticity, and conventionality within music. Silver et al (2022) find that artists must balance between the conventions of a gene and the innovations of unconventionalities. They find that genre listeners are punitive of those who innovate too much but reward those who hit a sweet spot mid-range between familiar and unfamiliar. The speculation behind this is that innovation dilutes the identity of the artist and their music and brandish them ambiguous or no longer part of a defined genre (see also Mark 1998; 2003). This demonstrates the discernment of cultural consumers and their inclination towards clearly identifiable boundaries. Artists who innovate too much dilute the clarity of their belonging to the genre. The results in this study suggest a slightly different mechanism, the dilution of affiliation. This effect is represented by the results drawn from the nonlinear relationships between centrality and success. Certain low levels of collaborative embeddedness are rewarded with greater career success. However, being overly embedded, in other words, collaborating with lots of other artists, or being overly central among other artists overshadows the focal artist and diminishes their success. This suggests, like Silver and colleagues' (2022) findings on the dilution of music through over innovation, that artist's identity is lost through their over affiliation. Therefore, artists interested in collaborating with others must balance their collaborative works with their solo works to avoid becoming overly embedded. This finding offers a plethora of future study opportunities. Foremost, discovering how this operates with in-genre compared to out-genre collaborations. The penalty of over affiliation among same-genre artists may be sharper because listeners engaged in a genre may desire artists to have bounded identities within their genre. Meanwhile, out-genre collaborations may follow a similar pattern as Silver et al. (2022) describes since artists may be penalised for collaborative rather than musical innovations and unconventionalities that out-collaborations brings (e.g. Grime artist Stormzy working with pop artist Ed Sheeran in their song 'Take me back to London' or 'Own it'). The sensitivity of these nonlinear relationships (i.e. how sharp the curves are) reflects the tolerance of listeners based on the actions of the artists. One important aspect to note about these findings is that despite having a statistically significant multiplicative effect, the goodness of fit of the nonlinear models compared to the linear models as indicated by the R-squared increases only slightly. Therefore, extrapolations of these findings should be made conservatively. Despite this, the findings still suggest that over embeddedness leads to diminishing returns on a Grime artist's career success.

Finally, this study builds on the collaboration literature by extending the scholarly knowledge of how embedded network relations influence career success. Deshmane and Martínez-de-Albéniz (2023) highlight the role of product augmentation through collaboration. Their study demonstrates that collaborated songs do better on the radio than solo songs. The assumption behind this is that two professionals work together and make a better song. Further, that the song is consumed by the followers of all collaborating artists. They also find that degree centrality is highly associated with more radio plays as well. The current study builds on this in two main ways. First, it focusses fully on exploring network-related mechanisms behind the career success of musicians. Doing so builds on the collaboration literature by extending the knowledge of network-related benefits in collaborative teams (Burt et al 2022; Yakubovich & Burg 2019; Mora-Cantallops & Sicilia 2019) into music. Second, the current study focuses on the actions of listeners. Measuring radio plays captures the mainstreams success of collaborated songs based on the actions of intermediaries like radio stations who decide what to play. Meanwhile, this study focuses on the decisions of fans and listeners by capturing the raw streams, popularity, monthly listeners, and followers of an artist. Spotify also acts as an intermediary by promoting artists through playlists (Aguiar & Waldfogel 2021; Morgan 2020; Prey et al 2022; Richi et al. 2017; Siles et al. 2022; Werner 2020). However, the outcomes measured in this study represent the decisions of consumers to engage with the content of an artist. Scraping the playlist data from the songstats.com API enabled me to control for the intermediary effect that Spotify may have in promoting some artists over others.

This study has several limitations. Foremost is that it is limited to one genre. The impact of network position or embeddedness may operate differently in different genres (see South et al. 2020). Comparing across genres would better capture the effects of network centrality and success in the industry rather than just Grime. Any differences observed across genres would indicate the differences in taste and behaviour among the niches of listeners associated to the genre (like South et al. 2020). Another limitation is that this study only looks at success on Spotify. While streaming services are very popular, there are still other avenues for career success such as through radio, endorsements, merchandise, and others. Limiting the study to Spotify enabled a closed case of collaboration and success on Spotify. However, the conclusions drawn from the study about embeddedness and career success are most appropriately discussed as collaboration and success on streaming services. Finally, the case may be exceptional. Grime as a grassroots genre may be an exceptional case for such a study. Grime is known for its high frequency interaction between artists since its inception with multiple artists sharing radio sets, live shows, and recordings (see Charles 2018; Target 2019). Such case-based research is limited to the confines and characteristics of the case. Future studies may attempt similar research across cases to compare Grime with other genres.

To conclude, the study provides evidence that network position in a genre of music is associated with career success. Specifically, the prominence of artists through their degree centrality and eigen centrality is the primary mechanism of embeddedness that drives success. However, the paradox of embeddedness also operates in Grime. Being overly embedded diminishes an artist's success likely through a dilution of identity through over affiliation. Artists interested in collaboration must balance their collaborative efforts with their solo work in order to avoid a dilution of their identity and therefore success.

CHAPTER 5: STREAMS OF COLLABORATORS: UK GRIME AND THE DIRECTION OF COLLABORATION ON STREAMING SERVICES

Abstract

This chapter adopts the exchange approach to collaboration and examines two ways that collaboration facilitates access to resources in music. The way collaborations between artists occur changes over time with streaming services becoming the main please artists release songs today. Previously, artists would work together on records or CDs and featuring artists would appear only on the host's album. Today, using streaming services like Spotify means that artists have profiles that house their discography. Featuring artists appear on the profile of the host. Listeners of one artist can quickly access the featuring artists because the profiles of collaborators are linked on each song. The current paper examines this feature of modern streaming services and theorises two ways that it facilitates access to resources by adopting logic from social network theory. Specifically, the chapter adopts the idea that connections between nodes are directed into outgoing and incoming arcs. From this I theorise that the direction of the collaboration on streaming services provides different career-related benefits. First that outgoing collaborations (appearing on another's profile) expands the resource reach of artists. Second, that incoming collaborations (another artist appearing on a host's profile) provide the host artist with a greater reputation through the power of nomination.

Introduction

"*See a feature with me on (fire), fantastic, flame on, spray a million bars and shower man (fire)*"

(JME featured on Chip: Ignite)

Collaborating with others augments the process of work and the product of work. Working in teams can streamline the production process as workers share responsibility of the project. As workers interact, they share resources with each other that can streamline the production process and the quality of the final product (Alsharo 2017; Burt et al. 2022; Leahey and Reikowsky 2008). With the introduction and growth of technology, now, many workers rarely interaction in person with others, but rather collaboration occurs online using platforms.

Platforms have changed the nature of work and the way that people work together (Cristea & Leonardi 2019; Ravenelle 2017; 2019; Yang et al. 2022). Platforms are online spaces that facilitate interaction between workers (i.e. Zoom meetings), or that directly connect consumers and producers/servers (e.g. DoorDash). The adoption of such technologies has been documented across myriad different industries from commerce (Yang et al. 2022), to e-sports (Burt 2012; Mora-Cantallops & Sicilia 2018; 2019), to the gig-economy (Ravenelle 2017), even to freelance work (Schwartz 2018) and online coders (Zöller et al. 2020).

Each platform has unique ways that it structures interactions between workers, whether streamlining communications into department-specialised silos (Yang et al. 2020), or through high frequency resource sharing interactions between randomly assigned teams (Mora-Cantallops & Sicilia 2018). Such studies suggests that the platforms facilitate specific types of collaboration, or that the structure of the platform influences the type of success that workers experience thereon. However, few scholars have directly engaged in measuring how platforms influence the way that collaboration affects career success. This study turns to the music industry as one of the first industries to adopt the usage of platforms to streamline producers to consumers through streaming services and build models to explore how such streaming services streamline the benefits of collaborating with others.

Using data scraped from songstats.com’s API on the career success of Grime artists with profiles coupled with hand coded collaborative connections between, the study explores the role of platforms - in this case streaming services like Spotify - in facilitating the benefits of collaboration in music. Specifically, it borrows the logic of expansion and nomination from the social networks literature (see Wasserman & Faust 1994: 129). Specifically, it operationalises collaborations in terms of building a nomination of reputation through indegree collaborations (other artists featuring on focal artist's profile) and in terms of expanding the resource reach through outdegree collaborations (appearing on the profile of others). The results provide evidence that collaborating on platforms positively impacts career success of artists. Further, they demonstrate that streaming services like Spotify provide have multiple mechanisms through which collaboration influences success.

Background Literature

Transitioning Workplaces and the Way Workers Interact.

The nature of work has changed to streamline the production of goods and services straight to the consumers. This process has hollowed out the middleman. In other words, companies and organizations have found means to remove mediators in the sale process. By so doing, producers drive their products straight to consumers removing the costs of intermediaries. With this movement there has arisen the platform economy (Wladawsky-Berger 2016) and the use of applications to streamlines services from a producer to the consumer. Sociologists of work allude to this as the sharing economy (Ravenelle 2017; 2019) where workers perform task-based labour that involves a direct contact from a consumer to a provider of the good or service. A classic example is DoorDash where a consumer makes an order for some food to be delivered and a DoorDash worker accepts the task and delivers the food. Platforms have changed the way that workers interact with each other.

In many instances, research on collaboration focuses on the interchange between individuals who are either physically present with each other or directly interact with each other (Ali et al. 2021; Burt et al. 2022) However, across many industries, workers use platforms to facilitate group work and team efforts are coordinated often without ever meeting (Alsharo et al. 2017; Burt 2012; Mora-Cantallops & Sicilia 2018). The advancement of technology means that workers interact with colleagues in a more specialized way. For example, examining the communication among remote workers, Yang et al. (2022) found that communication became more asynchronous and more siloed into departmental groups. In other words, the use of platforms to facilitate remote work changed the way that workers collaborate encouraging less communication across interdepartmental groups. Using remote tools decreased the extent to which workers were connected others in the workplace leading to a decrease in communication and social capital between employees. However, other studies found that professional freelance workers who work exclusively on task-based work often through platforms develop alternative methods to collaborate with others. Schwartz (2018) finds that freelancers develop a network of other professionals who meet via platforms. Through these platforms, freelancers find means to share resources and develop professional skills and connections. Thus, platforms have changed the way that workers interact with others, facilitating new methods for interaction.

Each platform has unique characteristics that facilitate the collaborative efforts of workers and the benefits of collaboration differ based on the platform. For example, online e-sports professionals who do not directly engage with one another in person, but through online groups that are often randomly assigned, benefit from low levels of centralized power. Mora-Cantallops and Sicilia (2019) find that high intensity interaction among players, but a low centralization of power and resources drive team success. Meanwhile, the hoarding of opportunities and resources in such environments benefits only the individual player. In this environment, then, assisting each other directly and sharing opportunities and resources is imperative for team performance. Meanwhile, coding professionals who interact through data repositories such as GitHub interact through pull requests that clone data stores so that individuals can suggest edits and make review. In this environment, the efficiency of coding pulls, edits, and reviews relies on the coreness of individual coders to the project (i.e. their centrality to the network), and their frequency of interaction (El Mezouar et al. 2019).

Collaboration, Platforms, and Potential Mechanisms in Music

One of the first industries to introduce this type of streamlined process of sale was the music industry. In the mid to early 2000s iTunes, Spotify, and later Amazon music, streamlined the consumption of music. Previously, consumers had to go to a shop and purchase an artist's CD. With the introduction of streaming services online, consumers now directly access an artist's music and as much music as is available on their platform of choice. The streaming platforms removed the necessity for record shops and even working with a record label who would often drive an artist's success on radio and in sales. Now, an artist's success on these platforms is driven by the consumers, namely the number of times a consumer streams their music. The platform connects the artist (the producer of the music) with the listeners (consumers).

The introduction of such services has generated much interest in how success is achieved through these platforms. Success on such streaming platforms can be influenced by more than just the consumers. Streaming services have flooded the market with an abundance of music and musicians because they have streamlined the connections between artists and listeners. There are multiple tools that streaming services use to drive an artist's success. One of the mechanisms that drives an artist's success is through playlist algorithms that streaming services use. Such algorithms to produce playlists of popular artists for the consumers (Aguiar & Waldfogel 2021; Morgan 2020; Pichl et al. 2017; Prey et al 2022; Siles et al. 2022). These services also create personally packaged playlists for consumers based on their music preferences. These algorithms can boost an artist's exposure to consumers and drive their success. The benefits of playlists, however, are not equally distributed and often exclude already marginalized artists (Werner 2020).

Thus, such services have introduced many unique mechanisms of career success that previously were not relevant. However, little is known about how these platforms impact the success of collaborative work. While research on collaboration in traditional settings state that it can augment the quality of the product and process, the current study explores some of the benefits of collaboration in the music industry that are specific to the usage of streaming platforms. Note, the study does not explore how the introduction influenced the instances of, or the processes associated with collaboration, but rather how the platforms themselves influence the benefits of collaboration. Specifically, this study borrows logic from the social networks literature and explores two potential mechanisms that the platform facilitates. By so doing, it tests how platforms affects the benefits of collaboration between workers in the music industry.

Prior to the invention of streaming services, musicians' success relied upon the sale of albums, merchandise, and concerts. Success in the industry was largely determined by intermediaries like record labels and radios. Artists are signed to a record label that leverages their connections with radio platforms to spread the notoriety of artists. Collaboration in such an instance was made contractually between record labels and housed in the albums of the hosting profile. Listening to an artist's CD exposes listeners to the songs they performed solo and with featuring artists. If consumers wanted to listen to the music of the featuring artists, they would purchase their CDs or listen to them on the radio. Recent research demonstrates that collaborated songs get more radio plays (Deshmane and Martinez-de-Albeniz 2023). The listeners of the host and featuring artist(s) want to listen to the song so the song is listened to more.

Nowadays, however, through streaming services consumers buy-in through a subscription fee and access hundreds of thousands of artists and millions of songs. These platforms, arguably, provide a way to streamline the benefits of collaborating with other artists. Success on streaming services relies on the direct consumption of listeners. Consumers, therefore, drive the success of artists by streaming the artist's content. The more streams an artist receives, the more successful they are. Although, a multitude of studies demonstrates that streaming services still play an intermediary role by deciding which artists get the most exposure through playlists (Aguiar & Waldfogel 2021; Morgan 2020; Pichl et al. 2017; Prey et al 2022; Siles et al. 2022). This continues to reinforce inequalities across gender and genre biases (Werner 2020). Despite this, streaming services facilitate the direct consumption of artist content for music listeners.

Little has been done to fully explore the mechanisms that drive the benefits behind collaboration on these streaming services. Whereas previously collaborated songs have more radio plays due to the large pool of listeners (Deshmane and Martinez-de-Albeniz 2023), and the contractual leverage of record labels, streaming services provide a multitude of career success measures like number of streams, listener engagement through return listeners or subscribers, and artist popularity. Studying how collaboration on such services influences these success measures offers fine-grained insight into how collaborating on these platforms impact different elements of an artist's career success.

This study explores the influence of streaming platforms in driving the benefits of collaboration in a music genre. Rather than emphasising the tie between individual artists as the driver behind their career success, this section builds theory that centres streaming platforms as the context wherein the collaborative work is housed and consumed. It also builds out the mechanisms behind the platform and theorises how the platform facilitates two types of collaboration. First, expansions through outgoing collaborations and, second, the reputation building of incoming collaborations. Rather than comparing the extent to which an artist is collaborative vs. solo, the goals of the current study are thus: 1) Examine whether the positive effects of collaboration on radio plays (Deshmane and Martinez-de-Albeniz 2023) also occurs on streaming platforms. 2) To centre the context of the collaboration (online streaming services) by exploring direction of the collaboration as a potential mechanism driving career success on such services.

Current Study

Profiles as a CVs

"I Used To Spend Days On The Grind But It All Changed Now we get paid online" (Cadell: In My Prime)

The study centres an artist's profile as a space where they publish their work, present their identity, and provide listeners access to their work. An artist's profile is akin to an academic's CV where it houses and displays their work. Like the CV, a profile on a streaming platform like Spotify is a space whereon musicians signal their affiliation with other musicians by publishing their work with others. Listeners can visit an artist's profile, access their discography, and see the other artists who they have worked with. Listeners can also click on the names of featuring artists and access their profiles. Thus, any given profile whose artist has collaborated with others has doorways to the profiles of the collaborators and therefore can be considered gateways into their network of collaborators.

Focusing on an artist's success on a streaming service like Spotify centres the agency of listeners in connecting with their favourite artists' content. Measuring radio plays captures the number of times a radio station elected to play a song (see Deshmane and Martinez-de-Albeniz 2023), whereas measures on streaming services like Spotify captures individual listeners who decide to stream songs and engage with an artist. This more effectively captures people's consumption of the music, rather than the role of organizers like radio stations in perpetuating music. Further, Spotify offers multiple career success measures; the economic capital of streams (implied royalties from a stream count), the cultural notoriety and dominance of popularity, the size of a person's fanbase through subscribers, and return-listeners who listen to the artist monthly. The current study looks at artist-level data to explore the effects of collaborative works on artist's career success compared to others in the same genre to test whether the positive effects of collaboration operate the same way in this setting.

H1: Collaboration positively influences the career success of artists on streaming platforms.

The focus of Spotify and the artist's profile is central to the mechanisms explored in the current study. I explore two potential mechanisms through which collaboration may influence an artist's career success; *resource reach* through outdegree collaborations or *added reputation* through indegree collaborations. Collaboration in this context, while still focussing on artists working together on music, also captures the decisions of artists to display their work with other artists on their profile. The theory behind the resource reach and reputation by nomination mechanisms stems from the logic of outdegree and indegree connections in social networks. An outdegree connection between two nodes of a network measures the connections coming from a focal node to another (i.e. sending a text message). Meanwhile, indegree connections measure the number of connections incident on a focal node (i.e. receiving a text message). Wasserman & Faust (1994: 126) define in and out degree arcs in terms of popularity and expansiveness. In degree is a measure of popularity in the network (i.e. within the network of musicians, who is worked with the most) whereby others nominate the focal actor as important. One with many in degrees are highly popular in a group having been nominated by multiple alters. Out degree, however, nominates others as popular. Those with a high out degree are expanding their reach into others. The following sections builds on this logic by focussing on how streaming services provide out- and indegree like collaborations and theorises how expansiveness and popularity may serve to boost artists' career success on platforms.

Since the current study focusses on the role of the platform as the context for the collaboration, the directedness of the collaboration is operationalised in terms of appearing on an artist's profile. In the context of collaboration on a music platform like Spotify, those receiving the collaboration (the in degree) are being nominated by the featuring artist as popular or worthy of the featuring artist's work. Meanwhile, giving a collaboration (the out degree) means to nominate others while expanding the reach of the featuring artists into the listeners of the host's profile. Thus, the *direction* of collaborative exchanges in the context of the streaming platform may boost artist's success in different ways.

Mechanism 1: Expansing Resource Reach Through Outdegree Collaborations

Appearing on many profiles across a platform like Spotify increases the reach of an artist by exposing more listeners to their work. Increasing one's reach for resources is something that could potentially boost one's success simply by increasing the pool of listeners. Specifically, an artist appearing on another artist's profile exposes those who visit that profile to the featuring artist’s work and the listeners may then start streaming that featured artist’s work. As Figure 15 presents, Artist A appearing on Artist B’s profile through a collaboration exposes B’s listeners to Artist A. While this is not the only method through which listeners hear of other artists, it is a way that artists can gain exposure to a broader audience. In this instance, B’s listeners could choose to begin listening to A’s music. This is an example of how collaboration may provide access to rewards that are exogenous to the collaboration itself. In other words, A and B are not exchanging any resources themselves, but rather the collaborative connection between them, facilitated by the streaming platform, may lead to greater success for artists.

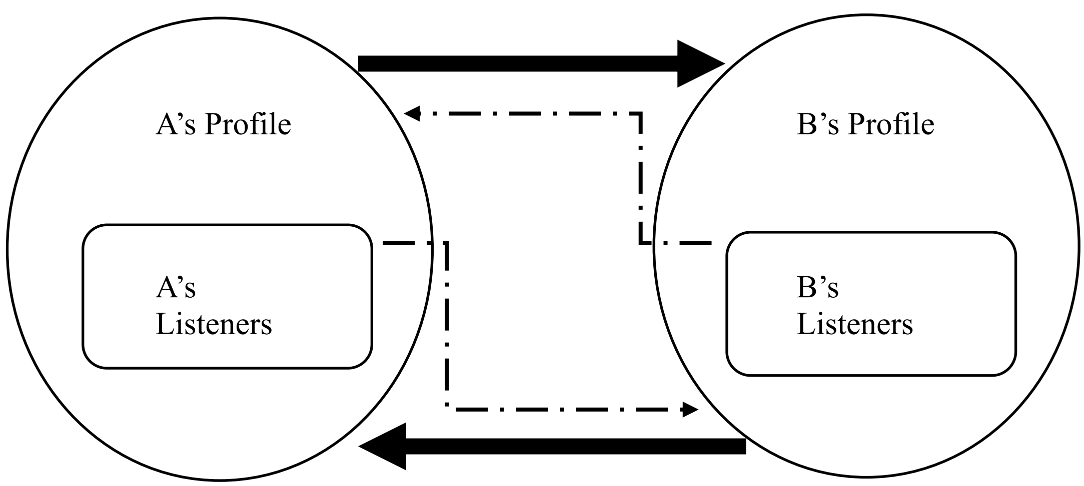


Figure 15: Potential Resource Reach Model in Music
Collaboration   Exposure for listeners

The current chapter explores this mechanism by examining the relationship between outdegree collaborations and artist’s success. An outdegree collaborative connection is when an artist appears on another artist's profile. Regardless of the rights to ownership of the song, the current study considers the appearance of non-profile artists as an outdegree collaboration. In other words, rather than an artist simply featuring on another artist’s song, whether they appear on the profile of another artist. For example, Artist B may feature (i.e. not own the rights to) a song of Artist A. If Artist B choses to publish that song on their own profile, this is counted as an outdegree collaboration for Artist A. Making more appearances on other artist's profiles increases the base from which artists can garner listeners.

Hypothesis 2: Outdegree collaborations increase the resource reach of artists.

Mechanism 2: Nomination and Reputation Through Indegree Collaborations

Reputation may facilitate career success because it drives popularity. Podolny (2008) argues that elite constituents in a market focus on building their recognition as elite through carefully signalling an elite status. Similarly, individuals build a brand name or reputation through carefully signalling their status through affiliation.

Studies of CVs/resumes indicate that they serve to demonstrate appropriate forms of capital to prove one a match for a job (Rivera 2012; Sharone 2013a; 2013b). One key function of a resume is the capacity to signal one's affiliation with desirable others and bring about the power of a name (c.f. Lin 2001). Likewise functions an artist's profile on streaming platforms because artists who have profiles with featuring artists may be considered more popular. Beyond popularity, listing songs performed with other artists also validates their position as a genre-artist and curries power to them through the names of their affiliates.

Deshmane and Martinez-de-Albeniz (2023) used a measure of degree centrality as an indicators of an artist's elite status within a genre. The current study extends this measure of by exploring a different approach that focusses on the transfer of resources rather than the structural position a person holds in a network. One of the ways that the reputation building of individuals occurs can be explained through the social capital literature and the power of a name. Lin (1999; 2001) explains that one of the ways social capital operates is to provide social credentials and reinforce identity. Specifically, collaborating with another artist and hosting them on a profile (indegree collaboration), adds a social credential associated with "the power of a name" from Lin’s (1999; 2001) theory of social capital, and may reinforce their identity as an elite constituent of the genre. In this manner, the incoming collaboration provides an individual a social credential, i.e., their connection to the collaborator, and a reinforcement of identity as a genre artist. Receiving an indegree collaboration from a genre-artist may credit the host with a reflection of their affiliation with that artist and the associated genre. This may bring further reputation to the artist and therefore build their fanbase.

Music listeners tend to group together and listen to musicians of their preferred genre (Mark 1998; 2003), the current study examines if artists can build their reputation by presenting the correct social credentials on their profile. Figure 16 demonstrates a potential model through which indegree collaborations may improve an artist's credential and reputation. When Artist A publishes collaborations with Artist B on their own profile, they signal their affiliation to Artist B. If an artist can successfully signal their affiliation with a genre through such collaborations, it may enhance the reputation of that artist and therefore their popularity.

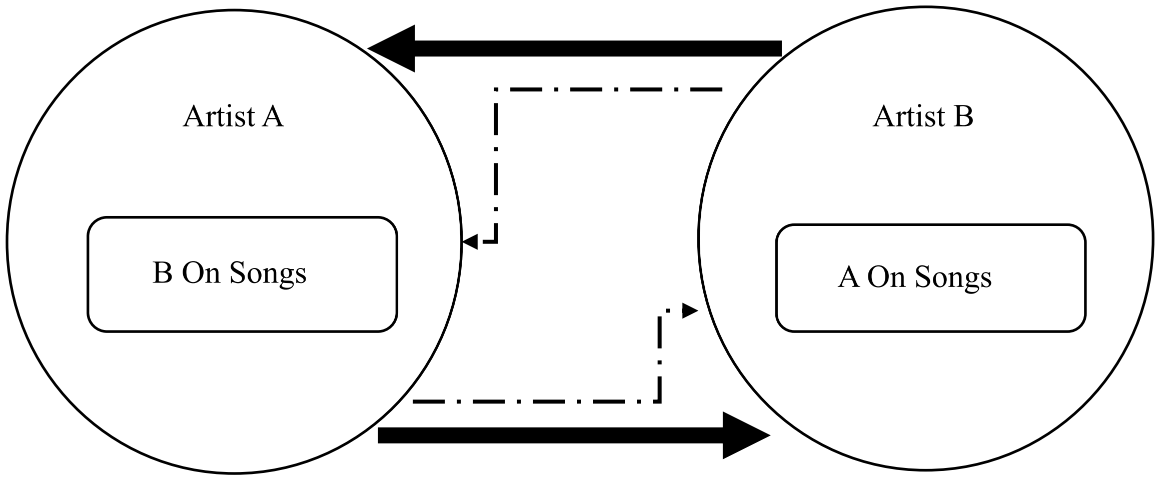


Figure 16: Potential Reputation Model in Music
Collaboration Add Reputation

The current study explores this mechanism by examining the relationship between indegree collaborations and career success. Contrary to the previously define outdegree collaborations, indegree collaborations are when artists feature other artists on their own profile. The logic is that the featuring artist nominates the host as a reputable member of the genre. That artists are collaborating on the host's songs indicates that they are worthy of the genre's attention. An example of how this may operate in such a scenario is if a listener visits a profile of an unknown artist and sees that they have songs with another artist known to them, they may choose to listen to the unknown artist because of the connection with the known artist. The host artist signals their status through their affiliation with others.

Hypothesis 3: Indegree collaborations boost an artist's career success.

This study addresses a limitation with studies in music that explore collaborative relationships which is the representation of artists disproportionally select for successful artists. Studies like Lena and Pachucki (2013) that uses data taken from the top 100 charts, or like Deshmane and Martinez-de-Albeniz (2023) that use radio plays select popular artists rather than represent artists across the distribution of success and notoriety. The challenge with going to charts and radio play is that the sample is of successful artists, i.e. those who got air-time or made it on the chart. Therefore, any extrapolations about the effects of collaboration must be limited to how it operates for the top-end of the distribution of artists. Not all artists get air-time, or make the charts, but those artists also collaborate. Thus, the current study explores artists from a range of success using multiple sampling methods to capture a representative sample of artists and explore how collaboration occurs across the whole distribution of successful and non-successful artists.

A further point on some studies sampling technique is that it captures and therefore compares collaborations across genres. Thus, samples include inter-genre vs. intra-genre collaborations. Genres collaborate differently (South et al. 2022) meaning that different genre listeners may respond differently to genre-artists collaborating in- vs. out-of-genre. In other words, classical music listeners may not appreciate classical music being performed with others while pop listeners may like the blending of two pop artists. Furthermore, to truly capture how collaboration operates in competitive environments, the constituents involved must be competing directly for the same resource. Thus, restricting the sample to one genre, or on in-genre collaborations only better captures the direct competition of genre-artists with other genre-artists, over genre-listeners. The current study limits the sample to one genre and strictly compares intra-genre collaborations to fully capture a competitive collaborative relationship.

Data and Methods

This study uses the sample of 122 grime artists discussed in Chapter 3. Unlike the first study in Chapter 4, this study only measures the collaborations within the sample. This limits potential spuriousness associated with the differences in collaborations across genres (South et al. 2020) or differences in consumer behaviours across genres (Silver et al. 2022). Therefore, the collaboration data used in this study are collaborations between artists in the sample and do not include artists outside the sample.

Dependent Variables

The dependent variables in the study are the same as from Chapter 4. Refer to Chapter 4 for a full explanation of each variable. In short, I measure *Artist popularity*, *Content engagement* through streams, *return listeners*, and *Listener engagement.*

Independent Variables.

This study examines three measures of artist-artist collaboration: First, t*otal Collaboration* - a count measure showing the total collaborations that an artist had with other in-sample artists each year. Second. outdegree *collaboration – a* measure that counts the number of times an artist appeared on another's profile within a year. Third, indegree *collaborations- a* count of how many collaborators from the sample that the artist published on their profile each year.

Control Variables.

The models control for *productivity*, *opportunity*, and *success* as do those in Chapter 4 1. Refer to Chapter 4 for a full description of each variable.

Analytic Strategy

The study begins by presenting descriptive statistics of the focal variables used in the models (Table 7). In Table 8 I test the hypotheses associated with collaboration, its mechanisms, and career success, with three sets of regression models. Models 1-8 test hypotheses 1a/b using ordinary least squares regressions of the total number of collaborations an artist did in a year predicting all dependent variables. Table 9 tests the first mechanism, resource reach through outdegree collaborations. This table takes the outdegree collaborations where an artist worked with another and was published on their profile and tests that across all dependent variables. Table 10 follows the same pattern but using indegree collaborations as the predictor.

The models throughout the results present fixed effects regressions run on available years provided on each variable. Since some dependent variables were collected later than others, these models have a smaller N. I recognised the uncertainty that comes when using fixed effects models with robust standard errors with a small sample size and therefore ran regular fixed effects regression models to compare. The results, along with the statistical significance were largely the same. I present the results from using the robust standard errors to demonstrate the robustness of these findings. Further, each model controls for variance across time. Each model controls for the number of years of observations available in `each model. Since the N is so small, I elected to control for years as a continuous variable to maximise the degrees of freedom in each model.

Appendix D and E also present some mediation models to examine whether there are different pathways associated with the type of collaboration on artist popularity. These models measure an artist's popularity and the explanatory power of the other career measures used in this study. Using nested regression models and the Sobel mediation test (Abu-Bader & Jones 2021), these appendices flesh out the mediation of streams, monthly listeners, and followers on the relationship between incoming and outgoing collaborations and artist popularity.

Results

Table 7: Descriptive Statistics for Career Success, Collaboration Type and Controls

Variable	Range	Mean/Proportions	Standard Deviation	N (n)
Popularity	5 - 88	48.90	17.08	414 (114)
Total Streams (Logged)	4.64 - 20.47	14.95	2.53	735 (119)
Total Monthly Listeners (Logged)	9.63 - 22.02	17.18	2.53	414 (114)
Total Followers (Logged)	8.86 - 20.53	15.56	2.33	414 (114)
Total Collaborations	0 - 46	2.77	4.86	735 (119)
Outdegree Collaborations	0 - 25	1.41	2.61	735 (119)
Indegree Collaboration	0 - 21	1.36	2.80	735 (119)
Total Songs	0 - 96	8.24	10.24	735 (119)
Playlist Reach Total (Logged)	13.80 - 24.39	20.38	2.04	414 (114)
Songs in Charts	0 - 16	0.40	1.38	735 (119)

Table 7 presents descriptive statistics for each of the variables included in the models. The mean (48.9) and the range (5 – 88) for popularity suggests that the artists in this sample are evenly distributed between highly popular and unpopular and that none have achieved the highest possible popularity (100). However, the standard deviation of 17.08 indicates that the sample is widely spread across the range of the variable. Meanwhile, the logged ranges and standard deviations for streams, monthly listeners, and followers indicate that the sample is widely distributed across these measures. Together, these descriptive statistics indicate that the sample includes both successful and unsuccessful artists – a realistic representation of genre artists (i.e. not all artists are successful).

The distribution of the collaboration variables indicate that Grime artists are very collaborative. With a range of 0 – 46 total collaborations, some artists in this group work with others a lot. However, the mean of total collaborations indicates that not every artist is very collaborative (only 2.77). Meanwhile, comparing the differences in the descriptives between out- and indegree collaborations suggests that artists appear more on another's profile (max 25) than host others on their (max 21). The rest of Table 7 presents descriptive statistics for the control variables.

Career Success and Collaboration

Results in Table 8 provide evidence that collaboration is positively associated with career success. Table 8 examines the effects of collaboration on career success and presents results from fixed effects ordinary least squares regressions of the total collaborations an artist has predicting their popularity (Models 1 and 2), their streams (Models 3 and 4), monthly listeners (Models 5 and 6) and followers (Models 7 and 8). Results in Models 1 indicates that collaboration and popularity are positively associated. In the bivariate model each additional collaboration an artist does is associated with an average increase of 0.12 in their popularity ($p < .01$). Although superficially this appears as a small effect size, considering that some artists may have upwards of 10 collaborations a year, the result can be substantively meaningful on their career success. This suggests that working with other genre artists boosts popularity. However, the positive effect of popularity is attenuated from 0.12 increase in popularity per additional collaboration to 0.2 when controlling for other factors. The effect of popularity is no longer statistically significant in Model 2 either. This suggests that the benefits of collaboration on popularity are largely explained through the artist's productivity, or that artists with more collaborations become more popular because they are placed on more Spotify playlists and have more songs in the chart.

Similarly, collaborating with other artists also boosts the number of people stream their music. Model 3 demonstrates that for each additional collaboration an artist performs there is an average increase of 2% (exp(0.02)) in streams. This suggests that working with other artists encourages people to listen to the music more, however, this effect is not statistically significant ($p > .05$). The effect of collaborations on streams remains non-significant in Model 4.

In addition to artist popularity and fan consumption of the artist's music, collaboration also boosts listeners engagement with the artist's content on Spotify. Model 5 shows that an increase in collaborations is associated with 4% (exp(0.04)) monthly listeners ($p < .001$). However, Model 6 shows that when controlling for other factors, an increase in collaborations is associated with a 2% increase in Monthly Listeners (exp(0.02)) ($p < .05$). Although this effect is attenuated, it shows that collaboration increase the return listeners that artists have.

Model 7 shows that collaboration boosts the number of followers artists have as well. Each collaboration increases the number of followers by 2% (exp(0.02)) ($p < .001$). Finally, Model 8 shows that an increase in collaborations is associated with a 2% increase in the number of followers (exp(0.02)) ($p < .01$). This finding is unchanged from the bivariate Model 7 suggesting that when controlling for productivity, opportunity, and success outside Spotify, collaboration remains a positive influence on listener loyalty through following.

Together the results in Table 8 provide evidence that collaboration increases a musician's popularity, and listener engagement through return listeners and followers. Essentially, the models in Table provide evidence to support Hypothesis 1, that collaboration follows much of the same pattern in the music industry among competitive same-genre artists as it does in other industries. However, the full models suggest that such benefits from collaboration are, at least in part, due to increased access to playlists, or success outside Spotify in the charts.

Table 8: Total Collaborations Predicting Career Success

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Popularity	Popularity	Streams (Logged)	Streams (Logged)	Monthly Listeners (Logged)	Monthly Listeners (Logged)	Followers (Logged)	Followers (Logged)
Total Collaborations	0.12**	0.02	0.02	0.00	0.04***	0.02*	0.02***	0.02*
	(0.04)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Songs Total		0.04		0.01**		0.00		0.00
		(0.03)		(0.01)		(0.01)		(0.01)
Playlist Reach (Logged)		4.13***		0.16***		0.76***		0.41**
		(0.65)		(0.03)		(0.11)		(0.13)
Songs In Chart		0.48*		0.07**		0.00		-0.02
		(0.23)		(0.02)		(0.03)		(0.03)
year	-0.67**	-1.06***	0.15***	0.02	0.07	-0.01	0.22***	0.17***
	(0.23)	(0.17)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Constant	1,394.88**	2,108.60***	-283.23***	-18.95	-129.78	31.45	-421.73***	-328.00***
	(461.24)	(342.20)	(53.15)	(57.97)	(81.42)	(65.50)	(76.43)	(61.16)
Observations	414	414	735	735	414	414	414	414
R-squared	0.07	0.33	0.16	0.31	0.06	0.26	0.15	0.21
Number of id	114	114	119	119	114	114	114	114

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.06, # p<0.07

The Mechanisms of Collaboration.

Resource Reach. Models in Table 9 test hypothesis 2 that outdegree collaborations increase career success by increases an artist's resource reach. The models follow the same structure of presentation as Table 8.

The results in Table 9 follow the same patterns as those presented in Table 8. Models 1 and 2 suggest that appearing on the profile of others is positively associated with popularity. Specifically, Model 1 indicates that every outdegree collaboration is associated with an increase in popularity of 0.2 ($p < .05$). Although apparently a modest effect, it must be interpreted under the understanding that artists appear on each other's profiles regularly and therefore this effect cumulates. Thus, appearing on the profile of another five times is associated with an average increase of 1 point of the popularity. When controlling for productivity, opportunity, and success outside of Spotify, however, this effect is largely attenuated (Model 2, $b = 0.08$) and no longer statistically significant. This suggests that, like in Table 2, those who appear on the profiles of others become more popular, in part, due to their greater exposure through Spotify playlists, and success outside the platform.

Models 3 and 4 show that appearing on other artist's profiles is not statistically significantly associated with more listener engagement through streaming. Model 3 indicates that an increase in outdegree collaboration is associated with a 2% increase in the streams of an artist, however, these are not significant ($p > .07$). Model 4 shows that this effect is explained when controlling for other factors.

However, artists who work on songs of other artists and appear on their profiles have more monthly listeners. Model 5 shows that an additional collaboration housed on another's profile is associated with a 6% increase in monthly listeners ($p < .01$). This means that listeners who see artists appearing on others' profiles are more likely to return. Or that appearing on the profile of another artist increases the reach of the focal artist and gives them access to the monthly listeners of the other artist (i.e. appearing on their profile gives the focal artist access to the host's monthly listeners). These findings remain statistically significant when controlling for other factors (Model 6, $b = 0.04$).

Additionally, those who appear on the profiles of other artists have more loyal listeners. Model 7 shows that an increase in outdegree collaboration expands the number of followers that an artist has. Every increase is associated with a 5% increase in the number of followers that an artist has ($p < .01$). Thus, listeners follow artists who appear on other artists' profiles. When controlling for the full model, an increase in the number of appearances on another's profile is associated with a 4% increase in the number of followers (Model 8, $p < .01$).

Results in Table 9 demonstrate significant support for hypothesis 2. Table 3 shows that artists who appear on the profile of other artists are more popular, have more returning listeners, and more followers. This suggests that appearing on the profile of others expands the resource reach of artists. As they appear on others' profiles, the listeners of the host profiles may begin listening to their work. Or they benefit from the engagement from the host artist's listeners.

Table 9: Outdegree Collaborations Predicting Career Success

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Popularity	Popularity	Streams (Logged)	Streams (Logged)	Monthly Listeners (Logged)	Monthly Listeners (Logged)	Followers (Logged)	Followers (Logged)
Outdegree Collaborations	0.20*	0.08	0.02	0.00	0.06**	0.04*	0.05**	0.04**
	(0.08)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Songs Total		0.04		0.01**		0.01		0.00
		(0.03)		(0.00)		(0.01)		(0.01)
Playlist Reach (Logged)		4.13***		0.16***		0.76***		0.41**
		(0.65)		(0.03)		(0.11)		(0.13)
Songs In Chart		0.47*		0.07**		-0.00		-0.03
		(0.23)		(0.02)		(0.03)		(0.03)
year	-0.66**	-1.06***	0.15***	0.02	0.07#	-0.01	0.22***	0.17***
	(0.23)	(0.17)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Constant	1,385.95**	2,108.30***	-281.88***	-19.00	-132.40	29.10	-424.00***	-329.41***
	(461.07)	(340.57)	(53.23)	(58.05)	(81.56)	(65.62)	(76.41)	(60.95)
Observations	414	414	735	735	414	414	414	414
R-squared	0.06	0.33	0.15	0.31	0.05	0.26	0.15	0.21
Number of id	114	114	119	119	114	114	114	114

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.06, # p<0.07

The Power of a Name. Table 10 presents the results testing hypothesis 3 that indegree collaborations boost artists career success through building their popularity because of the names they work with. The assumption is that having others work on music with them boosts their authenticity as an artist through the power of the names they are associated with.

The results in Table 10 suggest that, like the previous findings, that having other artists appear on a host's profile increases the popularity of the host. Model 1 shows that each time a featured artists appears on a host's profile, the host's popularity increased by 0.18 ($p < .05$). This suggests that listeners like artists who signal their affiliation with other artists. However, this finding is explained when controlling for other factors (Model 2, b = -.0.01, $p < .07$).

Meanwhile, unlike previous tests, indegree collaborations are associated with more listener engagement through streams. Model 3 shows that each indegree collaboration is associated with ana average increase of 3% in the number of times listeners stream the content of a host artist ($p < .07$). This suggests that hosting multiple other artists encourages listeners to engage more with the host artist's content. Furthermore, this finding stands out as particularly different from Tables 2 and 3 where those types of collaborations are not predictive of streams. This finding suggests that there are meaningful differences behind the types of collaborations that streaming services provide. Specifically, between the indegree power of nomination and outdegree expansion of resources reach. This positive association, however, is explained by the full model (Model 4).

Meanwhile, having more featuring artists on their profile boosts the number of monthly listeners by 6% (Model 5, $p < .001$). Fans return to listen to the content of artists who have their collaboration with other artists on their profile. When controlling for the full model, however, this effect is attenuated to a 3% increase ($p < .05$) suggesting that some of the benefits of indegree collaborations on monthly listeners is mediated through the full model. Specifically, Model 6 indicates that an artist who is on playlists that reach more people has more monthly listeners.

Finally, indegree collaborations are associated with having a larger following. Model 7 shows that each indegree collaboration is associated with an average increase of 3% in the number of followers that an artist has ($p < .01$). This finding is consistent with the results in the other tables suggesting, like other forms of collaboration, that indegree collaborations boost an artist's fanbase. This finding, however, is attenuated to 2% when controlling for the full model ($p > .07$). Unlike the other forms of collaboration explored in Tables 2 and 3, then, the benefits of indegree collaboration on followers are partially mediated through the full model as is the statistical significance of the main effect.

Results in Table 10 support hypothesis 3 that indegree collaborations are positively associated with career success. Specifically, they show that across all measures of career success indegree collaborations increase an artist's success. Furthermore, that indegree collaborations are associated with streams while all and outdegree collaborations are not, it is apparent that there are meaningful differences between these mechanisms. This provides some evidence that the power of nomination and building a reputation through publishing work with others on a host profile encourages listeners to engage more with their content.

Table 10: Indegree Collaborations Predicting Career Success

	(1) Popularity	(2) Popularity	(3) Streams (Logged)	(4) Streams (Logged)	(5) Monthly Listeners (Logged)	(6) Monthly Listeners (Logged)	(7) Followers (Logged)	(8) Followers (Logged)
Indegree Collaborations	0.18*	-0.01	0.03#	0.00	0.06***	0.03*	0.03**	0.02
	(0.08)	(0.07)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Songs Total		0.05		0.01**		0.00		0.00
		(0.03)		(0.01)		(0.01)		(0.01)
Playlist Reach (Logged)		4.14***		0.16***		0.76***		0.41**
		(0.66)		(0.03)		(0.11)		(0.13)
Songs In Chart		0.49*		0.07**		0.01		-0.02
		(0.23)		(0.02)		(0.03)		(0.03)
year	-0.67**	-1.06***	0.15***	0.02	0.07	-0.01	0.22***	0.17***
	(0.23)	(0.17)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
Constant	1,405.81**	2,104.15***	-283.43***	-18.86	-126.47	31.64	-419.78***	-328.66***
	(463.13)	(343.62)	(53.13)	(57.94)	(81.23)	(65.42)	(76.32)	(61.22)
Observations	414	414	735	735	414	414	414	414
R-squared	0.06	0.33	0.16	0.31	0.05	0.26	0.15	0.20
Number of id	114	114	119	119	114	114	114	114

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.06, # p<0.07

Discussion and Conclusions

The aim of the current paper is to explore how collaboration influences career success on music streaming platforms. Recent studies have explored how collaboration influences the popularity of musicians and of songs through radio (Deshmane & Martínez-de-Albéniz 2023). Using data collected from Spotify the study begins by exploring whether collaboration positively influences career success as it does in multiple other settings (Burt et al. 2022; Leahey 2016; Mora-Cantallops & Sicilia 2018; Zoller et al. 2020). It then builds on this knowledge by exploring two mechanisms through which collaboration may benefit artist: first the resource-reach of outdegree collaborations extending the exposure of artists to a broader base of listeners. Second the reputation garnered through indegree collaborations of other genre-artists adding legitimacy and authenticity to an artist and their profile. Finally, the study concludes by examining a third potential dilution effect of collaboration and career success by examining the three types of collaboration and whether they exert a nonlinear effect on career success.

The results show that collaboration is associated with multiple outcomes of career success. Specifically, Table 8 demonstrates that those with more collaborations are more popular, have a bigger listener fanbase, and more followers. This echoes much of the literature on collaboration outside of streaming services (Deshmane & Martínez-de-Albéniz 2023). Then, Tables 9 and 10 attempt to tease out potential mechanisms based on the logic of expansion through outgoing collaborations, and nomination of incoming collaborations. These tables show that both types of collaborations on streaming services are associated with career success. The only difference is that incoming, or indegree collaborations are associated with getting more streams whereas outdegree collaborations are not. This finding, although modest in effect size, suggests that there is a meaningful difference between the types of collaborations and that the streaming service facilitation of collaborative work in music influences different elements of an artist's success. This evidence warrants further investigation.

There are multiple limitations with this study. First, the differences between the two types of mechanisms across Tables 3 and 4 are marginal. Although suggestive of different pathways to success through the types of collaboration explored in this study, this is not enough to confidently conclude that the reputation model provides meaningfully different career results from the expansion of resource reach model. Second, there are other ways that artists are connected in genres that could also be considered incoming and outgoing collaboration. For example, an artist could help write, or produce another's work. Third, the findings presented here do not fully tease out the pathways of the effects of collaboration. There is a possibility that the benefits of outgoing collaboration on an artist's popularity is impacted because they gain more streams. Meanwhile, the effects of incoming collaborations on ana artists' popularity may be explained by that artist getting new followers and monthly listeners. These models could potentially better tease out the differences between incoming and outgoing collaborations in streaming services (see Appendices D and E).

Despite the limited representativeness and conclusiveness of the findings, the present study still makes multiple contributions to the literature on collaboration and music. By focussing on the streaming service and adopting the logic of social networks (Wasserman & Faust 1994), this study takes an important step into examining the fine-grained influences of platforms on collaboration benefits. The models of reputation and resource expansion can be applicable elsewhere and of greater use when exploring platforms and collaborations. For example, these models may be significantly more different when examining across genres of music. Expanding one's resource reach beyond their current genre through collaboration could positively boost an artist's success while building reputation from artists outside the genre could negatively impact an artist's career success due to the boundaries of conventionality around genres (Silver et al. 2022).

In conclusion, platforms influence the way that people interact and collaborate across multiple work settings. This study adds to the understanding of collaboration on platforms first by examining collaborations on music streaming services like Spotify and second by adopting a network perspective to examine the potential ways platforms streamline the benefits of collaborations in music.

CHAPTER R 6: GIVERS, TAKERS, AND RECIPROCATORS: THE RATIO OF INDIVIDUAL-TO-GROUP RECIPROCITY

Abstract

This chapter adopts the reciprocity approach to studying collaboration. An artist's relationship with their genre can be thought of in terms of their collaborative connections to others in the genre. This chapter explores an artist's connection to their genre by examining the extent to which their efforts are validated by others. To do this, this paper adopts logic taken from the scholarship on reciprocity. Network scholars find that reciprocal connections between collaborators generates bonds of trust, affective regard, and accountability. Measures of reciprocity in network studies focus on the relationship that exists between two individuals. The question remains; can we theorise a person's relationship to a group in terms of reciprocity? Further, is the *balance* of the connection between an individual and the group to which they belong associated with career success/advantage? This chapter is split into two parts. First, it builds a theoretical framework for measuring individual to group reciprocity. Second, it provides showcases testing the utility of the measure and exploring reciprocity as a mechanism for driving the benefits of collaboration in Grime.

Introduction

"*And in the end the love you take is equal to the love you make*" (Beatles – The End)

This chapter turns to reciprocity between groups and group constituents as the third potential mechanisms for driving the positive association between collaboration and career success in music. Borrowing logic from the social network's literature (Krackhardt 1987; Wasserman & Faust 1994), and the sociological understanding of exchange between persons (Bearman 1997: Molm 2010; Molm et al. 2007), this chapter builds a unique measure of signalling and validating group participation/investment by building a measure of individual-to-group reciprocity. Using the mechanisms of in- and out- degree connections between individuals, I operationalize these in terms of signals (outdegree connections) and validation (indegree connections). This is akin to Wasserman and Faust's (1994) original conceptualization of expansion (outdegree connections) and nominations (indegree connections) but contextualizes these mechanisms as an artist's willingness to participate in a genre and the genre's validation of their participation. The method borrows the structural map from Pescosolido and Reuben's (2000) spoked wheel of relationships which asserts that individuals are connected to groups of other individuals bound together by their foci (in this instance, the genre). The paper builds a theory of network exchanges from an individual to the group they are interacting with. The exchanges are based on the logic of signals and validation from the literature on identity and being (Mead 1969).

First, the paper discusses the theoretical foundations for signalling and validating through connection and exchange. It demonstrates why reciprocity is an appropriate way to measure a person's group-status (signalling participation or being validated by the group). It then lays out an equation for how to measure individual-to-group reciprocity. Second, it provides showcases using empirical tests to demonstrate the utility of the measure and an application of the theory to a case. Using data on Grime, a UK-based rap genre, the paper asks whether an artist's validated group status is associated with advantageous network position? And whether an artist's group status is associated with higher career success?

The collaborative connections between artists in a genre constitutes the genre itself. As artists interact with each other through collaboration they construct a network. This network of interacting artists builds a genre. The reciprocity of collaborative connections can validate the belonging of an individual to that genre. This chapter provides a method to demonstrate this through a ratio of artist (individual) to genre (group) connections. The varied extent of reciprocation between an artist and the genre substantiates an artist's status to the genre. Artists who receive more than they give could be conceived as popular or prominent artists within the genre. Meanwhile, those who give more than they get could be seen as the proponents of the genre. In other words, they act to ensure the genre's continuity.

The method proposed in the current paper can be used to better understand individual-to-group relationships. The logic of balancing in and outdegree connections to a group enables researchers to quantify people's willingness to signal their belonging to a group, and the group's efforts to validate their belonging. Such a method has powerful implications for research on inequality, exchange, and group status. Exploring who is validated by which groups based on individual-group demographics can explain more about how social closure or discrimination might occur. The current study theorises the method, provides an exemplar and concludes by discussing further uses for such a measure.

Background Literature

Collaboration to Construct a genre.

A genre of music is constructed through a complex process of developing the boundaries and conventions of the genre. First and perhaps most obviously, there are specific musicological conventions that differentiate one form of music from another. Conformity to these musical characteristics is an essential component for the establishment of musical genres (c.f. Schmutz & van Venrooij 2021; van Venrooij 2015). Artists wanting to participate in the genre must signal their legitimacy by adhering to the musical conventions associated with that genre (Peterson 1999; Silver et al. 2022). Therefore, musicians 'band together' (Lena 2014) and generate a genre of music as each individual artist reinforces the genre's conventions. This duality of artists and genres demonstrates a symbolic or indirect way in which artists collaborate to ensure the foundation and continuity of their genre. There are also other ways that artists work together to characterize genres and the conventions thereof. This section focusses on collaboration as the modus operandi for genre constitution.

A core group of prime movers collaborate to lay the fundamentals of a genre. In addition to the musical aspects of genre-building, the network of individual artists and the collaborative ties that exist between artists also constitute boundaries around a genre. Crossley's (2008) classic study of the emergence of the UK Punk scene explains the salience of connections between central actors who drove the birth of Punk. Crossley's findings suggest that in genres there is a central core of artists who work together to define the conventions of the genre and bring it out of obscurity into the mainstream. From the core develops a network of interconnected artists who band together and form the genre (see also Dedman 2011). Those central to the genre are those who drive its conventions and future.

Artists can also collaborate directly with other artists to ensure the success of music within their genre. Collaboration between artists can augment the success of the genre by sharing talent and pooling resources. For example, sharing musicians across jazz groups (Gleiser & Danon 2003) ensured the success of the jazz genre even in the face of social inequalities such as racial segregation. In this instance, the transfer of musicians from one group to another demonstrates the collaboration between individual constituents of the genre and their efforts maintain the genre's success. Over time, the efforts of individual artists to share talent with one another can ensure the group's continuity.

Artists can work directly with other artists on songs. Working together on a song brings together the skillset of more than one artist. In turn, this can augment the popularity of the song.

When artists collaborate, the song is listened to by the followers of each artist which then boosts the song's notoriety. For example, Deshmane & Martínez-de-Albéniz (2023) find that collaborated songs often receive more radio plays than solo songs. Therefore, collaborating with other artists to create music generates a buzz among the patrons of the genre causing it to thrive. In this case, the individual artists benefit directly from working together because their songs become more popular.

One final way that collaboration may also serve to ensure the genre's constitution and continuity is through constructing and maintaining a cultural image associated with the genre. Musicians can indirectly work with each other to produce a cohesive story associated with their genre. Storytelling through music is a historical aspect of genre-making. As new artists enter the music scene, they reinforce the story of the genre by signalling a shared lived experience in their own music (see Gibson 2014). Furthermore, there is a lineage of musicians that exist within a genre to whom artists pay homage. Hodson (2016) demonstrates that artists pay homage to others through shoutouts in their songs. Listeners, subsequently, perceive that there is a cohesive group of artists associated with that genre that share memory and lived experiences.

Each of these types of collaboration serves to construct the boundaries of a genre. Such collaborations include the planful action of individual artists within the genre to adhere to, reinforce, and ensure the success of the conventions of their genre. Thus, the collective action of individuals generates an aggregated benefit for the whole genre – it's perpetuity. In these instances, collaboration, in its many forms, is an essential mechanism through which genres are constructed and maintained. It follows, therefore, that collaborative connections between artists in a genre constitutes the genre itself. The group is meaningless without its individual constituents upholding the group conventions. As artists interact with each other through collaboration they construct a network. A genre of music, then, is a network of interacting artists (see Hodson 2016; Smith 2006; South et al. 2020) who, through many forms of collaboration, invest into their genre's success.

A key yet understudied element of genres and collaborative networks in music is the reciprocation of collaboration. Specifically, how the decision to reciprocate collaborative connections with other artists signals an individual artist's investment into the group. At the same time, individuals within an established group genre may wish to attract talent or validate the participation of others by investing in their music. This connection between an artist and the genre they participate in constitutes a symbolic connection of investment. It captures the extent to which they make efforts to work with others in their group and the extent to which others work with and invest in them. In what follows I argue that reciprocity in networks offers a way to measure and examine the relationship between an artist and their genre. In other words, reciprocity can be a tool for understanding an artist's level of investment into the genre and the genre's investment into the artist. The balance of this relationship creates categories or group statuses that can be demonstrative of an artist's acceptance into their genre. These group statuses may be associated with varying career success. An artist may see success depending on whether the genre validates them. I develop a theory on reciprocity, exchange, and validation to excavate why this may be.

Reciprocity, Exchange, and Investment

The current paper asks two questions. First, whether we can identify the extent to which an artist is invested into the genre and the genre into the artist by examining their reciprocity. Second, whether the extent of that investment is associated with career advantages. To successfully engage with this, I couple literature on reciprocity, exchange, and social network theory to contrive a method of reciprocity that can best capture the balance of an individual's relationship with their group. To begin, I turn to approaches on reciprocity and exchange.

Reciprocity is a social process of mutual interaction and exchange. In essence, reciprocity involves the exchange between two or more people with mutual benefit. There are two basic processes of measuring reciprocal exchanges, direct and generalized. Direct reciprocity involves a mutual exchange between two atoms who directly benefit each other (A <--> B), while generalized reciprocity includes at least one other actor. Generalized reciprocity involves an individual benefiting another and then being benefited by a third-party through a chain (A->B, B->C, C->A) (Molm 2010). Across these models, the assumption is that benefiting others precipitates a return benefit either directly from the receiver or indirectly through another. How reciprocity operates is a result of the context of the exchange.

All forms of reciprocity, therefore, rely on senders, receivers, and the item which is exchanged. An exchange rests on the senders' intentions, the actual exchange, and the receiver correctly interpreting the intentions of the sender. It may operate positively or negatively depending on the intentions and the interpretation thereof. Scholars assume that reciprocity, then, involves the rewarding of kind actions, and the punishing of negative ones (Falk & Fischbacher 2006). Exchange involves symbolism and interpretation of the intention, and the nature of reciprocity hinges on the receiver interpreting, not only the consequence of the action, but its intention. For example, research demonstrates that support received is directly affected by the support people render (Bowling et al. 2005) suggesting that positive actions incite reciprocal reactions from others. How ever it operates, whether directly or indirectly, reciprocity builds interpersonal positive affect and constitutes a primary mechanism behind building social solidarity in complex groups like societies (Bolton & Ockenfels 2000; Polanyi 2001). Further, the positive effects of reciprocity abate the negative effects of power imbalance that may operate in people's networks (Molm 2010). Scholars also argue that reciprocal exchange involves not only mutual benefit but that reciprocal exchange can operate regardless of a received benefit (Moody 2008) so long as actors reach equilibrium (Dufwenberg & Kirchsteiger 2004).

When teams collaborate in work settings, the mutual exchange of resources between individuals builds trust and accountability between collaborators (Burt et al. 2022). Further, over time the consistency of individuals feeling like their efforts are reciprocated by the efforts of other team members builds a strong affinity between collaborators (Yakubovich & Burg 2019). Additionally, worker's effort can be reciprocated with wages (Pereira et al. 2006). While positive reciprocal exchange helps maintain worker effort, negative exchanges have lasting effects on a person's effort that they exhibit at work (Kube et al. 2006).

There are instrumental, and symbolic values that reciprocity provides which can help explicate why collaboration is key to the continuity of genres. Instrumental exchange involves the direct benefit or benefits that are collected because of the exchange. For example, sharing musicians across bands (Gleiser & Danon 2003), or sharing talent on a song (Deshmane & Martínez-de-Albéniz 2023). Meanwhile, there are immaterial returns to reciprocal exchanges. Unsolicited exchange outside of formal agreements also generate a symbolic, expressive value for the actors involved. Such value can be measured in terms of strong trust and solidarity between those involved (Molm et al. 2007). Thus, reciprocity between artists in a genre could potentially generate cohesion between artists and ensure the continuity of the genre. The reciprocity of collaborative connections can validate the participation of an individual in that genre and signal the genre's investment into that individual artist. However, current approaches to measuring reciprocal exchanges are limited to dyadic exchanges. To examine the reciprocal collaborative exchanges between an individual artist and the genre, I need to go beyond considering reciprocity as a dyadic phenomenon.

Building a Theory of Individual-to-Group Reciprocity

There are multiple measures for reciprocal exchanges in networks, however, the preponderance measures the extent to which dyads are mutually connected. In an exchange between two individuals, scholars interested in people embedded in a directed network study whether the edge sent from i to j is returned. If an edge is returned in a directed network, then the relationship between the two nodes is considered balanced and therefore reciprocal (Holland & Leinhardt 1976). Scholars interested in the network itself use a ratio of mutual connections to generate a global measure of reciprocity (McMillan et al. 2022). This indicates the extent to which the observed ties in the network are mutual. The ratio used is measured such that a score of 1 suggests that all extant ties in the directed network are mutual. Both measures, whether local (dyadic) or global (network) rely on the extent to which edges are sent and received by individuals in the network. Such measures, therefore, capture only the direct forms of reciprocity, when something is given and received between a pair of actors. This section builds a theory of how indirect reciprocity can operate in networks to explain a relationship between an artist and the genre to which they belong. First, however, it is important to understand the context wherein the current measures of reciprocity stem from and that generating a new measure of reciprocity involves a nuanced perspective on where they stem from. They stem from the modern assumptions of how social relations are structured.

The Structure of Social Relations. Simmel (1955) was among the first to study how individual social networks operate and argued that groups are nested into concentric circles. Simmel argued that group affiliation forms as people flock together because of propinquity, or under some other social focus (see also Feld 1981). Participation in the smallest of groups is contingent upon the participation or affiliation in the group above that. For example, a group of graduate students are connected to each other because of their mutual affiliation/participation to the department. Contemporaneous to their connection to others in the department, they are also affiliated with everyone at the university level. Here there are two groups, the larger, university-level, to which they are affiliated, and the smaller department-level group of graduate students. Simmel's approach highlighted an individual's participation or association to a group.

Moreno (1941) developed a slightly more refined version of how social relations are structured. Moreno did not necessarily refine any of Simmel's original theory of the web of affiliation, but instead focused on developing methods for measuring people's networks. Rather than capturing an individual's connection to a group, Moreno focused on the individual and developed reticular methods that portray a matrix of people's affiliation, known as a sociogram. Using matrices, Moreno mapped an individual's connection to other individuals in a reticular format opposing the concentric circles method of Simmel. Building this out, Moreno's sociometric approach to social network analysis provided the means to generate a true web or matrix of people's connections to other individuals. Any subgroups that exist within such a network can be measured inductively by comparing the density of clusters within the network to the global density of the network itself (Blondel et al. 2008; Girvan & Newman 2002; Kapferer 1972). Using this method, an entire university can be mapped out into a matrix visualizing the connectivity or interaction of individual students in the university. From that network, the group of nodes connected to other nodes, community detection methods could identify the graduate student group mentioned above. Thus, rather than considering the nested group affiliation approach of Simmel's concentric circles, Moreno's matrix looks at and maps out individual affiliations. Much of the focus on social network analysis has adopted Moreno's sociometry approach generating individual-based social networks (e.g. Bearman & Parigi 2004; Brashears 2014). Current measures of reciprocity rely on this approach to measuring people's social network.

To best measure an artist's mutual investment and reciprocity of their connection to their genre, I need to develop a method outside of the social network theories that rely on the reticular structure of sociograms. Pescosolido and Ruben's (2000) theory of a spoked wheel of relationships brought back an argument for how people's affiliations are structured into nests that capture both individuals and groups of individuals. This is where an individual's network is neither made up of concentric circles nor is it a web of individuals. Rather, Pescosolido and Ruben likened it to a spoked wheel whereby a central ego, or individual, is tethered to groups of individuals. In this example, individuals are in the centre of their own network (rather than the central group - Simmel) and are connected by an edge to a larger circle, or group, of other individuals. Carrying on the above example of graduate students, rather than Simmel's approach of being a graduate student nested in a university, or an individual tied to other individuals, the spoked wheel approach would show an individual connected to the department which includes all the individuals in the department.

This paper builds a measure of reciprocity that assumes the spoked wheel of relations approach to social relations. Much of the literature on reciprocity relies on a Moreno-based sociogram that highlights the symmetry of networks through chains of exchange (Bearman 1997), and the mutuality of connections between dyadic in a network (McMillian et a. 2022). Instead of the dyadic and the chains of reciprocity, the spoked wheel of relations enables a form of reciprocity that captures an individual's relationship to an entire group. It is a nuanced form of reciprocity whereby one can send to a group, then receive from anyone in that group (i.e. not in the chain format of Bearman's reciprocity of A ->B, B->C, C -> A). In lay terms, the individual does something (sends an edge) to the group, and someone in that group does something for the individual (returns the edge). Such a measure of reciprocity underlines two types of action: the investment of an individual into the group and the validation of the individual by the group.

Individuals Invest and Groups Validate. In Georg Simmel's (1955) *Web of Affiliation* he claims that "as the person becomes affiliated with a social group, he surrenders himself to it. A synthesis of such object affiliations creates a group" (p. 141). Here, Simmel demonstrates that there is s reflexive mutual constitution between individuals and groups. That groups make an individual "surrender" themselves to it the conventions of the group, and that the group would not be without the individuals (see also Breiger 1974). Thus, the individual influences the identity of the group, and the group influences the identity of the individual. The surrendering of an artist involves their investment into the conventions of the music (Lena 2014; Peterson 1999; Silver et al. 2022) and the investment into direct or indirect collaborations with others in the genre to ensure the genre success.

Meanwhile, groups play a role in validating the identity ad participation of individual constituents. Mead's (1969) theory argues that the identity of individuals is something that is constructed over time through interaction. He theorized that the expectations, behaviours, and validations from others influence one's concept self. For Mead, a cyclical progression occurs as people internalise the attitudes and outward actions of others and choose to act in accordance with what they perceive their role to be in the group they affiliate with. Mead argues that "the self … is essentially a social structure" (p.205) and that "a person is a personality because he belongs to a community" (Mead 1969, P.226). A simple example is captured in the sociology of sports literature. People perceive themselves as players of a new sport when their peer group confirms it for them (Coakley & Donnelly 1999, p.67). In other words, the new identity that involves playing a new sport is internalised when validated by others.

Signalling one's desire to conform to the conventionalities of a group requires the effort of an individual. The reciprocation of that effort by group members legitimizes the individual's participation. In the previous example in sports, the desire to be a rugby player requires an individual to join a team and participate in that team (Coakley & Donnelly 1999, p.67). The identity, however, of the individual comes when they have accepted to conventions of the group (surrendering themselves to the group as Simmel put) and is validated by the attitudes and behaviours of the group (Mead's interactionism of self and others). Such an event demonstrates a reciprocal exchange – the individual signalling their participation, and the group validating those efforts. This exchange can involve multiple attempts and efforts from both the individual and the group. When applied to music, the choices of artists in a genre to work on songs with another validates the receiving artist's legitimate participation in that group.

Considering an artist's connection to the genre as following a single tether from a node to the group, outdegree connection from the artist constitutes them "giving" the genre a signal or willingness to participate in or affiliate. This outdegree effort could be a communication between artist and an affiliate, their conformity to genre conventions, or it could be the direct work of an artist on the work of a genre affiliate. This effort from the artist constitutes the same logic as Simmel's (1955) "surrendering" themselves to the genre and conforming to the conventions of the group. Meanwhile, if a group were to reciprocate the outdegree efforts of an individual, they would validate the efforts of the artist as a part of that group. Such a validation may generate the "in" status of the individual and therefore construct the dual ties between the individuals that they directly work with and others who affiliate with the group. This can be simplified into a tie between an individual and the whole group. The extent to which that tie is balanced can be measured in terms of a ratio.

Building a Measure of Individual-to-Group Reciprocity

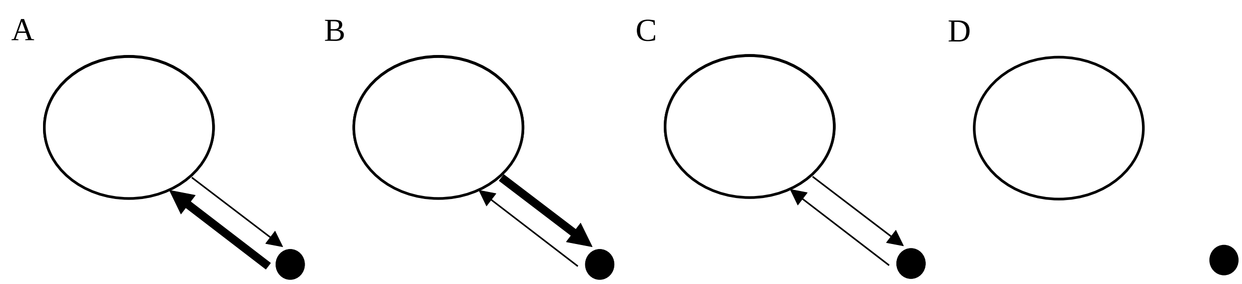
Very simply, the measure of reciprocity used in this paper is a division of a person's total outdegree by their total indegree ties. This measure considers the reciprocity between an individual node (i) and the entire network. To accomplish this, first we need to abstract an individual's connections to other individuals into a measure of their connections with the whole group. The way that we do this is to isolate and sum the indegree (d_o) and outdegree (d_i) sends from each node. Put simply, this is a count of how many connections are sent from a node (outdegree), and how many it receives (indegree) (Wasserman & Faust 1994: 125). At this point. each node has two values - their indegree and their outdegree. The next step is to divide their outdegree by their indegree to derive a ratio of how many an individual sends vs. how many they receive. This constitutes the status of the individual and the group relationship (see Equation 1).

$$\text{Equation 1: Individual-Group reciprocity} = \frac{\Sigma d_o}{\Sigma d_i}$$

A ratio with values above 1 indicates the node receives more than they give (more indegree than outdegree connections). Below one, the person gives more than they receive. Exactly 1 indicates perfect replication of individual to group, while a null response individual the person is not a group participant. These categories can be conceptually defined as givers, takers, and reciprocators. Each category themselves offers opportunity for interesting study. For example, exploring what characteristics predict becoming a giver, taker, or reciprocator within different groups. Meanwhile, and individual with no incoming or outgoing ties is isolated from the group.

Figure 17 visualises these reciprocality status categories. The black circle represents an individual while the larger white circle represents a group. The arrows represent in- or outdegree connections and the thickness of the arrow correlates to the number the directed edges one has with the group. From left to right, first in panel A, those who have a value higher than 1 they have more out than they do in. These “net givers” spend most efforts giving to that group. For example, a sociologist who constantly works on the research of others could be a “net giver.” Second in panel B, those with a value below 1 have more in from the group than they do out to the group. These “net takers” take more from the group than they give to the group. To carry the example, a sociologist who receives help on their research projects more than they give to help others could be a “net taker.” Rather than focusing on the connotations associated with “givers” and “takers” in society, such a measure takes the net in vs. out and how much they send to vs. receive from their group. The third group in panel C are those with a measure of 1 which means they have a one-to-one ratio for every indegree to every outdegree. These, “reciprocators” return every indegree they receive from their group on a one-to-one ratio. Panel D visually represents those with zero incoming and zero outgoing connections to the group.

Figure 17: Visualising Individual-to-Group Reciprocity



There may be instances where nodes have only an indegree or an outdegree value. To deal with such cases I suggest replacing their null value on as 0.001 to avoid an incalculable division. For example, a node with 1 out and 0 in has more out than in and is substantively meaningful to the study (a taker from the group). However, 1/0 does not work mathematically. However, 1/.001 > 1 which, when interpreted, indicates that node receives more than they give from the group and is therefore valid for such usage.

This measure can also be used with longitudinal network data. With longitudinal network data, each node has in- and outdegree connections at each time of observation. The cross-sectional approach described in Equation 1 may be used to explore the dynamism of one's group status. In other words, comparing one's group status at T1 with their status a T2… TK casts a trajectory of group status over time. However, there may be instances where the nodes in the network remain the same and a cumulative approach to one's group status is more appropriate. The cumulation of indegree and outdegree connections over time constitutes a person's present group status. To measure this, one simply cumulatively sums the outdegree and indegree connections before dividing them (see Equation 2). This provides a cumulative ratio of one's group status as of TK where K represents the last time of observation.

Equation 2: Cumulative Individual-Group Reciprocity = $\frac{(\Sigma d_o T1)+(\Sigma d_o T2)....+(\Sigma d_o TK)}{(\Sigma d_i T1)+(\Sigma d_i T2)....+(\Sigma d_i TK)}$

This measure relies on two major assumptions. First, for the measure to truly capture a person's effort and the groups effort, there must be a clear definition between in- and out- degree connections. This distinction between what the individual does and what is done to the individual must be substantively meaningful. For example, sending and receiving an email in a work environment, there is a clear sender and receiver. Second, there must be a clearly defined group with whom individuals are connecting. Beyond the individuals in the network, there must be a shared or desired affiliation between the individuals in the network. For example, players in a sports team, collaborators in work team, members of a church group, artists in a music genre etc. Each of these examples have a clearly define group that individuals may wish to participate in.

While other measures of reciprocity focus on the mutuality that exists between individual nodes (i,j) in a network, this measure looks at the mutuality that exists between a single node and the entire network, specifically all those with whom they interact. Instead of counting mutual edges that exist between individuals, the function of this measure generates statuses of exchange relationships between individuals the group they engage with by grouping all indegree and all outdegree and comparing the ratio between the two. Abstracting these exchanges in such a way shifts the focus from individual relationships (i.e. between dyadic pairs) and focuses on the status of an individual in relation to the group. This approach adopts the structural framework of Pescosolido and Ruben's (2000) individual-to-group relationships in a spoked wheel of relations. It also treats reciprocity as a standard that people either meet, exceed, or fall short.

In essence, the current measure provides a metric of an individual's or a group's reciprocality. Reciprocality, by definition, is a status of giving and receiving which relies upon both parties involved with the exchange to oblige to the exchange relationship. A person cannot be reciprocal unless they give and receive. Under the terms of direct reciprocity, the reciprocality of and individual is contingent upon themselves and the individual with whom they exchange. Under such a direct relationship, a person who gives cannot be reciprocal unless they receive from the person they gave to. Under the generalised, or indirect conceptualization of reciprocity, a person's reciprocality is also contingent upon the actions of the one with whom they initially exchange. In these terms, the recipient must give to another in a chain before the one receives, and the exchange becomes reciprocal. Under such terms, a person is considered reciprocal when they cause a chain of exchange and receive their benefit from another (not the initial recipient). However, under the terms of the individual-to-group reciprocity outlined in the current study, an individual's reciprocality is contingent upon the group. Rather than relying on the actions of the immediate recipient, the individual can be considered in a reciprocal relationship with their group if they receive a connection from any individual in the group. As such, the theory captures the reciprocality of the individual as they relate to the group in which they are participating. A person has a reciprocal relationship with their group when an outdegree by the individual is returned by any other from the group. By extension, the person remains reciprocal with their group when all outdegrees towards the group are returned by any in the group. The three categories provided by the current measure of reciprocity captures the story of the individual, and the group efforts of exchange and the reciprocality of both. Thus, it delineates reciprocality into role-like qualities of net-giving, net-taking, and reciprocating.

Showcase 1

In Showcase 1 I demonstrate the process of measuring a Grime artist's relationship with the genre in terms of their group reciprocity. Specifically, the showcase demonstrates the usage of the cumulative ratio by summing an artist's total out degree collaborations and dividing it by the total in degree collaborations from within the 22-year period I collected (discussed in Chapter 3). In this case, such a method yields 4 groups, givers (<1), takers (>1), reciprocators (1), and those with no Grime collaborations. For the purposes of this paper these in the last group are solo artists although they may have collaboration ties other artists outside of the sample. I selected to use the cumulative approach to measuring an artist's reciprocity to capture their level of investment over time. In other words, an artist's relationships with collaborators in T1 do not reset in T2 but rather their investment into the genre continues and builds over the years.

Figure 18 visualises how the groups change over time throughout the evolution of the genre. The line colours in the graph present the four categories and the y axis is a count of the number of artists who have a ratio to match those categories. The purple line on the graph shows that artist-to-genre reciprocity is exceptional in this group with the only six as the highest number of artists being around 2013.Meanwhile, there is a steady increase in givers and takers to the genre. The blue line demonstrates a steady increase in givers during the early years of the genre till 2015 when it levels off. Substantively, this demonstrates that during the nascent years of the genre many artists were working on the songs of other artists. This could be representative of artists' efforts to drive a cohesive scene and to feed the emergence of the genre by validating other artists. The green line shows a sharp curve lower than the line of givers between 2001 and 2012 indicating that the genre's early years are characterised by efforts to work on other's songs more than to take from others. However, between 2012 and 2015 there was a period where the genre had more takers than givers. This period is often considered the heyday of Grime music with the rise of artists like Stormzy on to the world stage (Target 2019; Stormzy 2018). Finally, the red line shows that there was a sharp increase in artists who had no Grime collaborations around 2007 and 2012 suggesting that Grime artists during these years were mostly solo artists. Alternatively, they could have collaborations outside the genre, and this could be a period where the genre diverged from its roots.

Figure 18: Line Graph Showing Reciprocity Categories Over Time

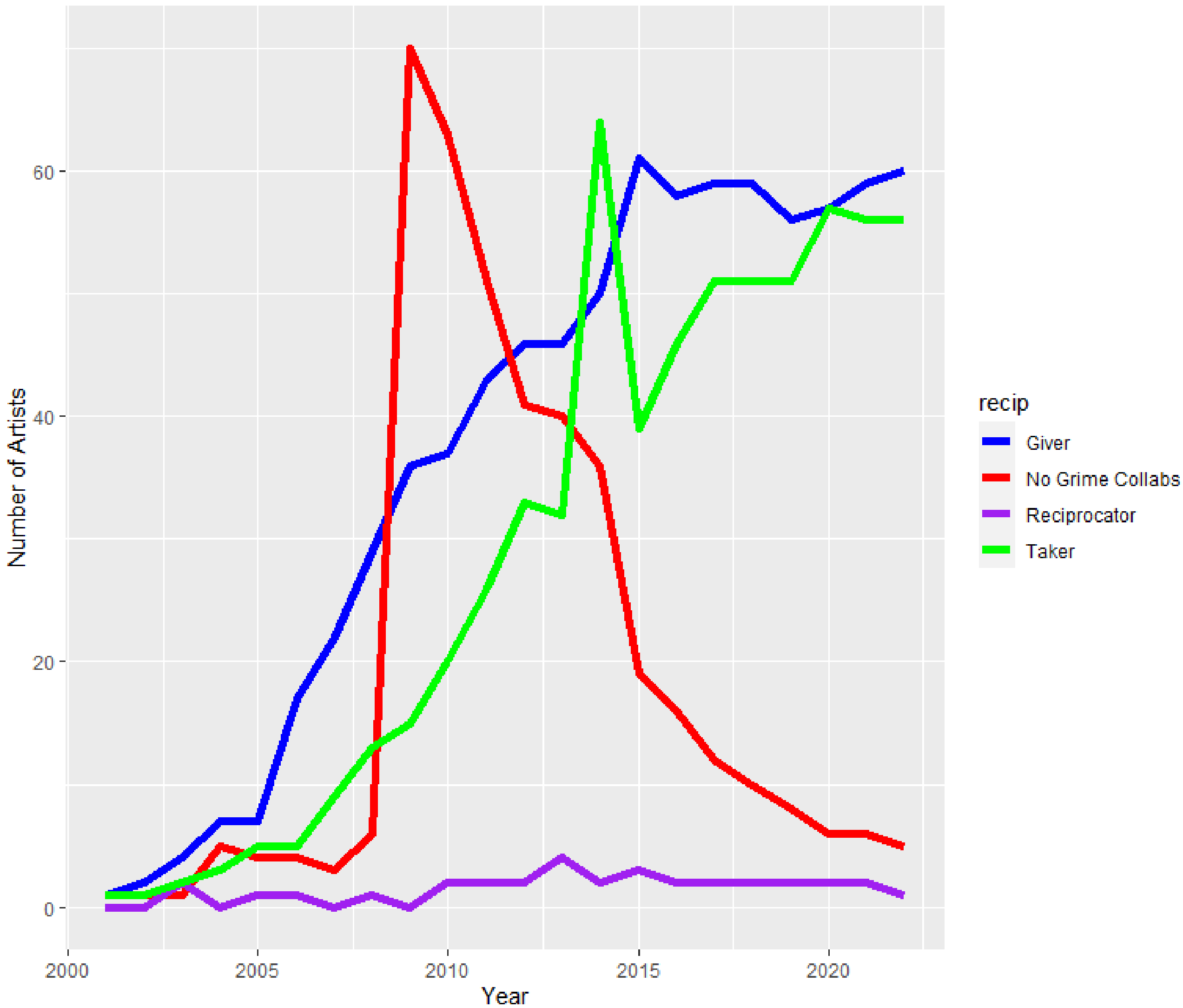
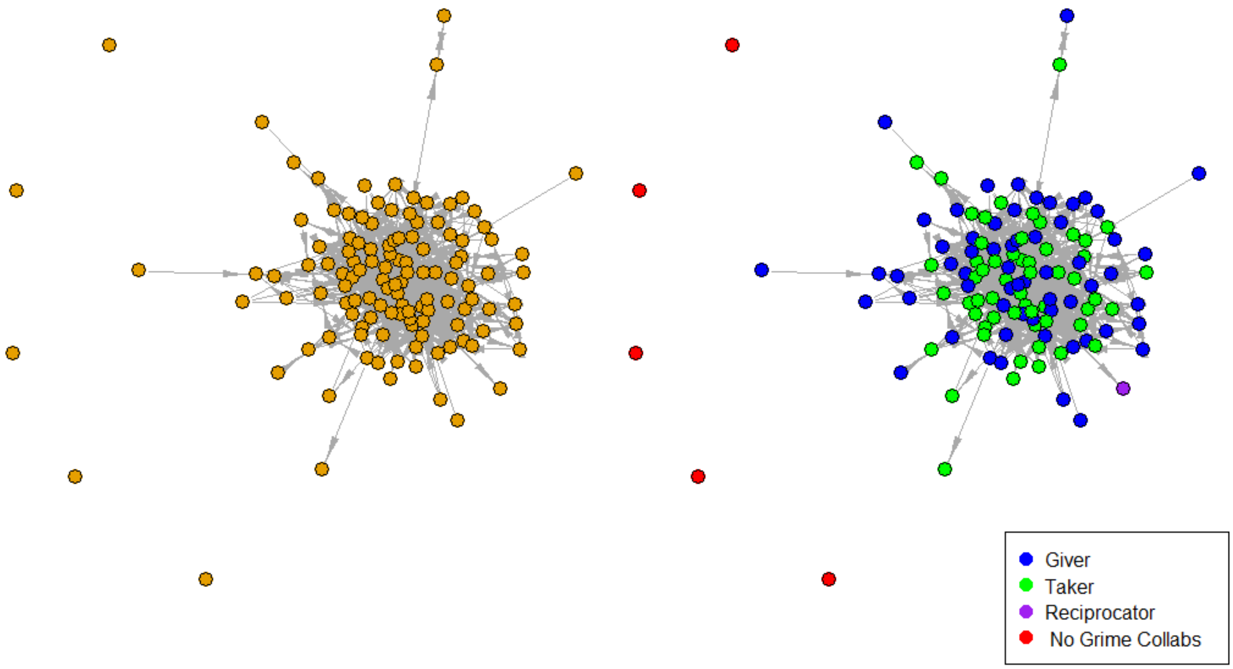


Figure 18 shows how informative the measure of reciprocity can be, especially when considered over time. It demonstrates the relationships of artists with the genre and how those relationships become more prevalent as the genre evolves (see Lena & Peterson 2008). This type of analysis could be very interesting to compare the prevalence of these roles across different genres. In Grime, it appears that givers were the more consistently prevalent. However, in other genres, maybe takers or reciprocators are more so.

Another use of this measure is to apply it as a node level characteristic to networks to examine the topology of the network in tandem with the distribution of artists who fulfil these different roles within the genre. Figure 19 shows two network maps of the Grime artists with their cumulative collaborative ties from 2001, or the beginning of their Spotify career, till 2022. The panel on the right presents the group with each artist's group status presented by the colour of the node. This map shows those who, from 2001 or the start of their career, are givers, takers, reciprocators, or who have no collaborations with fellow Grime artists in the sample as of 2022.

It appears that the group is constructed by a densely connected core with a secondary outer ring of artists and a tertiary ring of artists connected only to one in the centre. The map on the right shows only one artist is perfectly reciprocal (purple node on the bottom right of the graph), there are five isolated solo artists (red), while the rest are either net givers or takers. A rough estimate of this map from visual inspection suggests that takers are more central to the group than givers are with more green nodes in the densely connected core group.

Figure 19: Grime Collaboration Network and Artist Group Status



Artist to artist collaborations Grime 2022

Artist to artist collaborations Grime 2022 by Category

At this point I have established a theory and a method for measuring an individual's relationship to the group. Specifically, an artist to their genre. Figures 18 and 19 demonstrate descriptive utility of this measure when examining a genre over time and as a network. I have, therefore, answered the first research question of the paper and demonstrated that we can derive an artist's investment into the genre through a division of their total out- and indegree collaborations with others in the group. This leads to the second research question of the current paper – whether the level of investment an artist shows is associated with career advantageous for them. To answer this, I present a second showcase based on the same case-study of grime artists.

Showcase 2

In showcase 2 I take the longitudinal data presented in showcase 1 and develop models to examine any associations between the degree to which an artist is reciprocally invested into the genre and career success. In what follows I outline the research questions tested, and the measures used in this showcase.

Empirical Tests

The above Figure 19 shows the cumulative collaborations in Grime from 2001 till 2022 and overlays the artist level reciprocity status as a node level characteristic. As previously mentioned, it appears that takers are more central to the genre. This first empirical test examines whether there is a statistically significant association that central roles in a genre are filled more by those who have more indegree than outdegree connections. Specifically, I examine an artist's degree centrality as a measure of their prominence within the genre. I also measure the extent to which these artists are constrained by the network. This tests whether one level of reciprocity is associated with strong redundant connections to others in the genre or whether there is a type of reciprocity that lends itself to looser connections that bridge otherwise unconnected subgroups or artists.

> *Question 1: Is an artist's group reciprocity related to advantageous network position in Grime?*

The second test examines whether the type of reciprocity that an artist has with their genre is associated with greater career success. It could be possible that those who have more outgoing than incoming connections to others in the genre are more successful because they are perceived by genre patrons as the "feeders" of the genre. Conversely, those who have more incoming than outgoing may be perceived as "endowed" or "nominated" by the genre and therefore be more popular. Seeing as reciprocators are so exceptional in the genre (see Figure 18) it may mean that these artists are the posterchildren of the genre. Such veneration may translate to more listener engagement. Chapters 4 and 5 use many career success measures. For the sake of parsimony, I only test the artist streams as a measure for the level of engagement an artist receives from listeners.

Question 2: Are Successful Artists givers, takers, or Reciprocators?

Dependent Variables

Degree Centrality: A measure of network centrality that counts the total number of neighbours of each node.

Constraint: A measure of node-level constraint taken from Burt (2004)'s concept of structural holes. It is a measure on how mutual and strong a node's ties are in terms of the constraint they place on the node. High levels of constraint indicate a node is highly embedded in the network and does not fill a structural hole. Low constraint indicates a node bridges two or more otherwise unconnected groups.

Streams: A measure of the total number of streams an artist had each year. This variable is logged to account for its uneven distribution.

Independent Variable

Reciprocity: This showcase uses the same cumulative measure of reciprocity used in Showcase 1 only it has separate observations for each year. In this instance, an artist's reciprocity status accumulates year to year and each year is used in the models as separate observation periods.

Table 11 presents descriptive statistics for the variables used throughout the models in the tests.

Table 11: Descriptive Statistics for Showcase 2

Variable	Range	Mean/Proportions	Standard Deviation
Dependent Variables			
Degree Centrality (2001 - 2022)	0 – 17	1.63	2.42
Constraint (2001-2022)	0.1 – 1.05	0.67	0.32
Logged Total Streams (2015-2023)	0.69 – 20.47	13.52	3.44
Independent Variable			
Group Status (2001 - 2022)	*NA*	Giver: 43.81 Taker: 32.76 Reciprocator: 1.55 No Grime Collabs: 21.88	NA

N = 122

Results

Question 1: Is an artist's group reciprocity role related to advantageous network position in Grime?

Table 12 shows fixed effects regressions using the group status to predict an artist's degree centrality in the collaboration networks across 22 years. Each model changes the base group to compare each category to the others. Model 1 shows that those with no Grime collaborations have significantly lower degree centrality over time ($p < .1$) than givers. This makes sense since they are isolates in the network. Meanwhile takers have are, on average, more central to the network than givers are ($b = 0.87$, $p < .001$). This suggests that those who have more in-collaborations than out collaborations are more prominent and central to the genre than those with more outdegree collaborations. Meanwhile, reciprocators are more central than givers. However, this effect is not statistically significant ($p > .1$) meaning this observation may be due to chance. Model 2 shows that the inverse is also true for the relationship between givers and takers (i.e. that givers are less central than takers). The remaining results in Table 12 provide evidence that the only statistically significant difference worthy of discussion is between givers and takers. Across the three models, reciprocators are not significantly different from givers or takers, but givers are significantly less central than takers. However, the R^ reported across these models suggest that the group status only explains a small part of the variation in degree centrality. This test does not explain fully why some artists are more central than others, but it does show that group status is associated with network position.

Table 12: Fixed Effects OLS Regression of Group Status Predicting Degree Centrality

	Degree Centrality	Degree Centrality	Degree Centrality
Group Status	Model 1	Model 2	Model 3
No Grime Collabs	-0.58+	-1.45***	-1.01+
	(0.34)	(0.32)	(0.61)
Taker	0.87***	BASE	0.44
	(0.19)		(0.57)
Reciprocator	0.43	-0.44	BASE
	(0.58)	(0.57)	
Giver	BASE	-0.87***	-0.43
		(0.19)	(0.58)
Constant	1.31***	2.17***	1.74**
	(0.11)	(0.12)	(0.56)
Observations	1,464	1,464	1,464
R-squared	0.02	0.02	0.02
Number of id	122	122	122

Standard errors in parentheses
*** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.06 – p < 0.1

Table 13 explores a different aspect to group position, constraint. Constraint is a measure of how connected an ego’s network is. Constraint borrows logic from Burt’s (1995) concept of structural holes that indicates an ego of a network may be structurally advantaged if they broker two otherwise separate groups. They may become valuable to both groups as they bridge information or resources from one group to another. Alternatively, this position may generate new ideas because they have access to a flow of nonredundant information from diverse groups

(Burts 2004). Constraint is a measure of connections between the artists and whether how constrained they are by their connections. This measure is an inverse of structural holes where a high constraint indicates an ego is highly connected and embedded within a network. Meanwhile, a low constraint indicates that the ego has structural holes in their network. In this instance, structural holes could be conceptualized as spanning groups within the genre.

The results in Table 13 indicate that the group status of Grime artists is associated with the structural holes in their network. Model 1 compares takers and reciprocators to givers. On average, takers are less constrained than givers ($p < .001$) meaning that they have more structural holes than givers do. Givers, therefore, are more constrained by those in their network are than takers are. This means that those who receive more than they give have more structural holes in their network and are, therefore, more likely to access nonredundant information than those who give more than they receive. Meanwhile, reciprocators are not statistically more or less constrained by the connections in their networks than givers (Model 1). However, they have greeter constraint, on average, compared to takers (Model 2, $p < .1$). Those who have a reciprocal relationship with all they work with. therefore, are more constrained than those who receive more than they give.

Table 13: Fixed effects OLS Regression of Group Status Predicting Constraint

	Constraint	Constraint
Group Status		
No Grime Collabs (Omitted)		
Taker	-0.21***	BASE
	(0.03)	
Reciprocator	0.01	0.22+
	(0.12)	(0.12)
Giver	BASE	0.21***
		(0.03)
Constant	0.76***	0.55***
	(0.02)	(0.02)
Observations	817	817
R-squared	0.05	0.05
Number of id	117	117

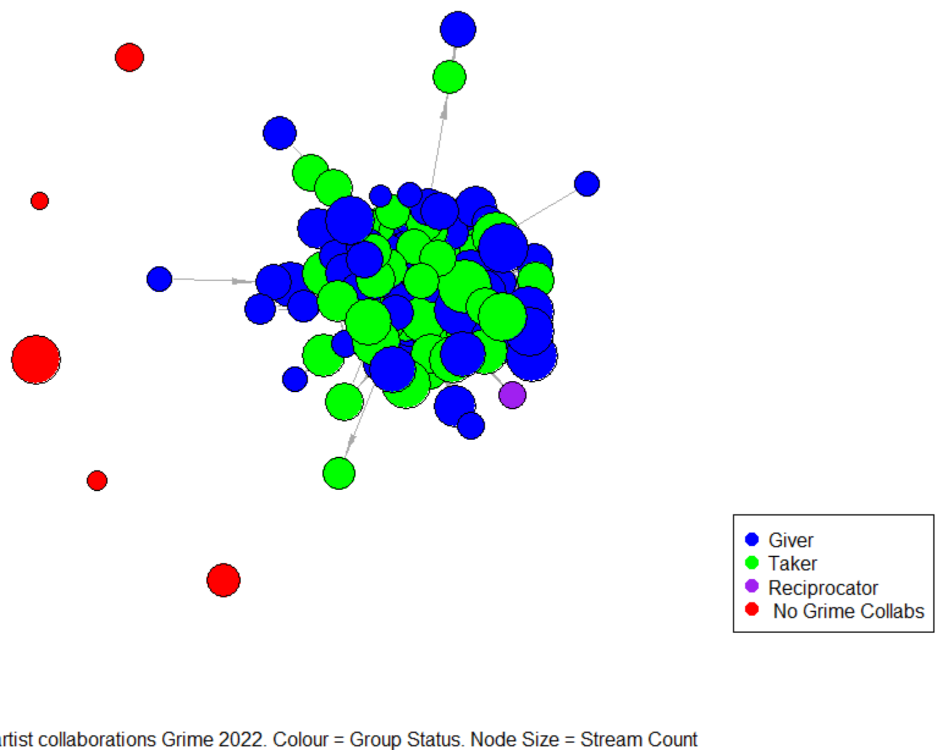
Standard errors in parentheses, 5 isolated nodes missing from N.
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.06 – p < 0.1$

In sum, the results across Tables 12 and 13 provide evidence that group status is associated with network position. Those who take more than they give in the group tend to be more central to the network but are less constrained by their connections to the network than those who give more than they receive. This could serve as a double advantage for takers when it comes to the benefits of collaborations since they are more likely to feature prominently in the group and their network is more likely to be structured in such a way as to generate new ideas and non-redundant information which may then, in turn, influence their desirability to be worked with continually. These two tests demonstrate the utility of the measure as well as the use in conceiving the connections among people and groups in terms of balancing what they give with what they receive. Tables 2 and 3 show that how an ego balances their relationship with the group influences their advantageous position within the group in terms of prominence and structural holes.

Question 2: Are Successful Artists givers, takers, or Reciprocators?

Figure 20 presents the network map shown in Figure 18 but alters the node size to present the artist's number of streams in 2022. It is unclear from this cross-sectional map whether artists from one group status are more successful than from other group statuses. The sizes of the nodes appear to vary within groups and across groups. However, this may be so because the measure of stream was logged. Findings in Table 14 may be more demonstrative of how these are related over time.

Figure 20: Grime Collaboration Network by Group Status and Streams



In Table 14, results show that givers are less successful than takers but are more successful than those who are of equal reciprocating status with the genre. Results in Model 1 show that takers have twice the number of streams than givers ($\exp(0.74) = 2.10$, $p < .001$). Likewise in Model 3 Takers have 6 times as many streams than reciprocators ($\exp(2.06) = 7.85$, $p < .001$). Meanwhile givers have significantly more streams than reciprocators (Model 1) and more than those with no collaborations. Finally, reciprocators have fewer streams than givers (Model 1) and takers (Model 2) but more than those with no collaborations (Model 3). In sum, these models show that takers are the most successful, followed by giver, then reciprocators, and finally those with not collaborations to the group.

Table 14: Fixed Effects Models of Group Status Predicting Artist Streams on Spotify

	Streams (Logged)	Streams (Logged)	Streams (Logged)
Group Status	Model 1	Model 2	Model 3
No Grime Collabs	-2.56***	-3.29***	-1.23+
	(0.33)	(0.32)	(0.66)
Taker	0.74***	BASE	2.06***
	(0.20)		(0.60)
Reciprocator	-1.33*	-2.06***	BASE
	(0.61)	(0.60)	
Giver	BASE	-0.74***	1.33*
		(0.20)	(0.61)
Constant	14.10***	14.84***	12.77***
	(0.11)	(0.11)	(0.59)
Observations	951	951	951
R-squared	0.12	0.12	0.12
Number of id	122	122	122

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p < 0.06 – p < 0.1

Discussion and Conclusions

This chapter asks two questions. First, can we identify the level of investment an artist has in a genre by exploring the balance of their collaboration with genre artists? Second, is the extent to which an artist is mutually connected to the genre associated with their career success? To answer the first question the paper explored a unique measure of reciprocity where individual artists are connected to the genre. Dovetailing theory on social exchange and reciprocity (Bearman 1997; Bearman et al 2004; Molm 2010; Molm et al. 2007) and theory on social networks (Moreno 1941; Pescosolido & Ruben 2000; Simmel 1955) and validation (Mead 1969: Donelly & Young 1999), the paper constructs a ratio of individual to group reciprocity. This ratio sums the total outgoing collaborations divided by the total incoming collaborations an artist has. This measure creates four distinct degrees of reciprocity. Those above 1 (more out than in) I call givers. Those below 1 (more in than out), I call takers. Those with a score of 1 are reciprocators, and those with no connections are solo or disconnected form the genre.

A key strength of measuring reciprocity in this manner is that it tells a story about individuals and groups. From the individual perspective, the four categories provide a measure to show whether individuals are taking, giving, or reciprocating to their group or whether they are disconnected from it. From the group perspective, the three categories show whether the group is validating the individual's position/participation in that group. Are they taking more from some than they are others? Or are they reciprocating to everyone on a one-to-one ratio? This offers several opportunities to study individual and group roles by way of their exchange relationships. First, the status of individuals, and second, which individuals do groups choose to validate. For example, are more prestigious individuals given more by their groups? The other side of that, do prestigious individuals take more from their group than non-prestigious people? From the group perspective, the measure provides, not an average likelihood of mutual ties in a group, but an indication of the group's status or relationship with every individual in the group. For example, the measure shows whether the group is returning the efforts of any focal individual. Such questions would be appropriately answered with such a measure: who do groups choose to work with or shut the doors on? In other words, are there certain individuals that groups elect not to validate and only accept sends from the individual (i.e. do not reciprocate)? Showcase 1 demonstrates that these categories provide a genre narrative when explored over time and when applied to the network as a node level characteristic. Showcase 2 demonstrates that the extent to which an artist has a mutual connection to the genre is associated with both advantageous position and career success.

The findings in this study suggest that those who receive more incoming than they give outgoing collaborations, takers, are structurally advantageous. These artists are nominated by their genre and this blatant endowment from artists in the genre places them in a very advantageous position within the group. They have significantly more degree centrality (prominence) within the genre, but significantly less constraint by their relationship the genre. This suggests that takers experience the competitive advantages of filling structural holes that provides access to nonredundant ties (Burt 1995) and good ideas (Burt 2004). It also means that they have the benefits of being highly central to the genre. A fact that Chapter 4 demonstrates is associated with greater career success. This endowment from the genre means that takers are also streamed more than givers, reciprocators, and solo artists in Grime.

Within sociological studies of culture and music there are three main applications of this paper. First, researchers may wish to replicate this type of measure and compare these models across different genres. Genres have different conventions and collaboration practices (Lena & Pachucki 2013; Hodson 2016; Smith 2006; Peterson 1999). Furthermore, the consumption patterns and tolerances to innovation, collaborative connections etc. differ across genres (Silver et al. 2022; South et al. 2020). Therefore, the prevalence of these different reciprocity groups may be very different across genres. Additionally, the extent to which takers, givers, reciprocators, and solo artists are successful may differ across genres. In some contexts, solo artists may be the most successful in genres where listeners prefer less mixing of artistic conventions. Such a test would inform on the collaborative investments of artists-in-genres and genres-in-artists across different cultural niches. Second, the next question that future researchers may wish to explore using this measure is who has access to the advantageous reciprocity statuses? In other words, who does the genre endow as a taker? Such studies would demonstrate whether traditional inequalities (see McMillian 2022) mean that these advantages are held only for those who fit the status value of the genre's culture. Third and finally, future researchers may wish to further this work by exploring the role of reciprocity in genre-building. Figure 18 demonstrates the prevalence of these roles over time. Archival studies may match these observation periods with the history of the genre and examine whether the roles were associated with different ongoings of the genre. Researchers may find that reciprocating the collaborations builds cohesion among artists and reifies the boundaries of their genre. Additionally, the reciprocation of collaborations may serve to purify the cultural practices of artists by ensuring they work together to maintain the social boundaries of their genre.

This measure of reciprocity and the models showcased in this study also has applications that extent beyond the scholarship on culture and music. One application of such a method is in the exploration of discriminatory practices among people. Replicating the method used in the showcases, researchers could determine whether ascriptive characteristics are associated with receiving validation from the group. Researchers could explore whether the exchanges made between workers in a team are balanced and whether those of an ethnic, racial, religious, or sex minority signal and receive the same way as those in the demographic majority. Studies of email exchanges, job applications/offers, promotion attempts, grievances etc. could be conceptualized as out- and -indegree connections between an individual and their work group. The signalling and validating behaviours of individuals and groups could reveal patterns of discrimination in such settings.

A second application and strength of this measure is its possibility for capturing the dynamism and evolution of exchange relationships over time. Rather than static measures of exchange, these measures over time can capture the dynamism of exchange relationships and how roles change over time. For example, there could be a progression of one's giving state to a state of reciprocity or taking from a group. In other words, testing the "grind" of entering a group. To become a sociologist, one must work on the research of others until a threshold is reached an others start to work on the work of the one and validate them. Scholars could use these categories to study the inequality behind the evolution of such roles. From this perspective, the distance or time between net giver, to reciprocal, or net taker may differ based on status or some ascriptive advantaged demographic. A simple example could be the length of time for a While, male sociologist to become validated by sociology as a group (either being reciprocated or by taking from the group) vs. non-White, female sociologists. The timing or the quantity/quality of the out vs. indegree exchanges can indicate inequality or follow unequal social norms. Likewise, the dynamism of social groups could also be interesting. How the events that occur within certain groups may influence the reciprocity of the group to individuals. Perhaps sociology is given a huge boost in popularity and funding and may open the doors to more budding sociologists.

A third application of this approach is to understand the competition of groups over group constituents. One limitation of the application of this method is that applying it within a group may be somewhat less theoretically interesting because each group member already has an in-group status as a group participant. In this case, each of these artists make Grime music. Meanwhile, a more appropriate application of this method may be to examine the changes in interactions across groups. McPherson's (1983) Blau Space provided a method to explore examine the competition of groups over participants. That approach looks at the demographics (age, education range, etc.) of participants and plots them in a 2-dimentional space to examine the overlap between groups. Or the probability of interaction based on homophily (McPherson & Smith 2019). In a similar inductive manner, the current method could be used to explore how interactions in one group influence an individual's interactions in another group. A change in the ratio between an individual and one group may cause a change in the ratio between the individual and the other group. In other words, signalling interest in one group while receiving validations from another may influence an individual to stop signalling interest in the first group. Likewise, a group may close itself off from individuals (stop sending to the individual) if the individual has participated in another group. In music, for example, an artist engages with a genre through collaboration in structured networks as demonstrated in this paper. If the artist were to collaborate beyond that genre into another, it may influence their relationship with the former. This approach deepens the scholarly understanding of competition between groups over group participants and the extent to which individuals attempt to span multiple groups. Furthermore, exploring the closure of some groups to participants can inform how sensitive some social groups are to category spanning compared to others. For example, in the religious context, an individual may be attending multiple churches. In this context, a congregation may decide to sever ties with the individual or to flock around them to keep them in the fold. The extent of the boundary spanning may influence the degree of response by the organization. In the previous example, if a person is attending multiple churches of the same religion (a close boundary span) or multiple churches of different religions (a far boundary span). Such utilization of the measure may look this this where Δ means "a change in":

Cross sectionally: Δ Individual-group reciprocity(group a) predicting Δ Individual-group reciprocity(group b)

Overtime: Δ Individual-group reciprocity(group a)T1 predicting Δ Individual-group reciprocity(group b)T2.

One major limitation of this paper is a possible tautology that exists between the assumption that people make up a group and people can be connected to a group. The paper argues that genres of music, at their core, are a group of interacting artists who collaborate directly or indirectly to construct the genre. This atomistic approach means that each individual artist is structural and cultural integral to the constitution of the group. However, I then argue that we can consider an individual artist and their connection to the group to extrapolate the extent to which they are invested and mutually connected to the group. In other words, that we can single out any individual from the genre (a group of individuals). This appears incongruous and represents a major limitation to the logic surrounding the assumptions behind the structure of individual-to-group relationships as being a spoked wheel of relations (Pescosolido & Ruben 2000).

Despite this, the paper begins a conversation on inductive ways to capture an individual's relationship to a group. The utility of the measure is not lessened because of the assumptions behind Pescosolido and Ruben's (2000) spoked wheel of relations. It represents a theoretical innovation to how we conceive the structure of people's relationships to groups and how that relationship can be balanced. The balance of that relationship can be operationalised in terms of an individual's validated participation in the group. This paper uses collaborative connections as the behaviour to examine and extrapolate. There are many other ways like genre conventionalities, connections outside the genre, alternate ties to artists like kinship, and others that can be explored.

To conclude, this paper produces theory and measurement of an individual-to-group reciprocal relationship. The inductive measure produced in this chapter can be used to examine the behaviour of individual in a group and the extent to which groups invest in individuals. The type of relationship that an individual has with their group is associated with various outcomes. In this instance, Grime artists who receive more than they give to the genre are structurally more central but less constrained by their group. They are also more successful in their career. These findings add nuance to the Beatles quote at the beginning of the chapter. Perhaps, in the end, love is given not made.

CHAPTER 7: DISCUSSION AND CONCLUSIONS

The aim of this dissertation is to explore potential mechanisms that drive the benefits of collaboration in music by adopting three perspectives to collaboration: network position, resource exchange, and reciprocity. Working together with other artists increases the success that musicians experience by boosting the radio plays of collaborated songs (Deshmane & Martínez-de-Albéniz 2023) or reinforcing the boundaries of their genre (Gleiser & Danon 2003; Lena 2014; Peterson 1999) ensuring its continuation. While a robust literature on the various ways that collaborating in pairs or teams influences career success exists (Alsharo et al. 2017; Burt et al. 2022; Cui et al. 2021; Leahey 2016), this dissertation seeks to focus on collaborations between musicians to extend the academic scholarship of collaboration further into the creative industries. The focus of the studies is on examining different elements to collaboration and how collaboration influences an artist's career success on the popular platform Spotify. Ultimately, across three empirical tests, this dissertation answers the question 'what mechanisms drive the benefits of collaboration on the career success of Grime artists?' Each chapter leverages themes of network position, the resources gained from collaboration, and the reciprocity of collaboration. The studies adopt a network perspective to collaboration and leverage network theory to excavate the mechanisms that drive the success of collaborative artists. Specifically, the dissertation theorises a genre in terms of a network of artists (nodes) and collaboration between artists as connections (edges). This section summarises the aims of each of the studies and discusses the results of each empirical test in terms of the primary focus of the dissertation.

First, study 1 in Chapter 4 leverages the well-known concept of network embeddedness and contends that network centrality is associated with increased career success. Network centrality in the context of music can be conceived of in terms of the degree of an artist's prominence within the genre, the influence they exert over the flow of information across the genre and the halo effect associated with collaborating with other influential artists.

The results from Chapter 4 show that network embeddedness is associated with career success in Grime. First, the degree of prominence in Grime is strongly associated with career success suggesting that listeners favour artists who are central to the genre. Second, the power of betweenness centrality also boosts and artist's fanbase, fan engagement, and popularity. Exerting some influence over the flow of information throughout the genre, therefore, is rewarded by listeners. Third, there was little evidence to support the halo effect behind collaborating with influential others. However, Chapter 4 also explored a potential paradox of embeddedness. Following Uzzi's (1997) classical concept of over embeddedness, the study tested whether being too embedded in the genre negatively impacted one's career success. The results showed a clear inverted u-shape relationship between the three centrality measures and multiple career success outcomes. This study concluded that being prominent and influential over the genre is rewarded by listeners. However, having too many collaborative connections with others diminishes the benefits of centrality. This dilution of affiliation likely occurs because listeners prefer clearly defined artistic categories (Silver et al. 2022) and too many collaborations dilute an artist's identity.

Study 1 in Chapter 4, therefore, demonstrates that collaborating in a genre of music can drive career success through the structural position that one fills within the group. If an artist can position themselves in a central, prominent position within the genre or in a position where they control the flow of information through the network, they are more successful. However, artists must balance their connectivity to others with their own solo work ensuring that their identity is not diluted.

Second, collaborations housed in music streaming platforms provide a chance to explore how the type of collaboration between artists influences different career outcomes. Study 2 in Chapter 5 borrows logic from the networks literature concerning the nomination of indegree connections and the expansion of outdegree connections (Wasserman & Faust 1994) and applies it to Spotify. Collaborations on Spotify can appear on a focal artist's profile, or the focal artist may appear on another's profile.

Chapter 5 highlights the context wherein collaboration occurs by focusing on the role that platforms play in streamlining collaborated works. Spotify as a streaming platform provides unique methods for driving artists' success, like the algorithms that drive playlists (Aguiar & Waldfogel 2021; Morgan 2020; Pichl et al. 2017; Prey et al 2022; Siles et al. 2022). This study borrows the expansion through outdegree connection, and the nomination of indegree connection from the network literature (Wasserman & Faust 1994) and conceptualizes outdegree collaboration as an expansion of the resource reach of artists. As they appear on the profiles of other artists on Spotify, they are exposed to the listeners of that profile and therefore expand *their* pool of potential listeners. Indegree collaborations can be seen as a nomination or reputation where other artists appear on the host profile building a proof of authentic belonging and an elite status in the group (c.f. Podolny 2008). This may build an artist's popularity and listener engagement as they are perceived as more prominent to the genre and an authentic genre artist. They are authenticated through their indegree connections or 'nominations' by other artists. The results from Chapter 5 show that both mechanisms are associated with career success outcomes which suggests that both in-and outdegree collaborations are positively associated with career success. There are some differences between which type of collaboration are associated with which career outcomes. Namely, that indegree collaborations are associated with an artist having more streams while outdegree collaborations are not. This finding, although a modest difference, provides some evidence that the mechanisms of in- and outdegree collaborations on Spotify offer different benefits to artists. Specifically, the nomination of indegree collaborations encourages listeners to engage more with the artist's songs. Meanwhile, outdegree expansion does not. Rather, outdegree expansion of resources is associated with gaining more followers and monthly listeners.

Chapter 5 relates to the main goal of the dissertation because it centres the context of the collaboration (Spotify) and examines how different types of collaboration on streaming services are associated with different resources needed for career success. This study theorises that collaborating in a network of peers involves a process of nominating others building their genre reputation and expanding one's resource reach through gaining access to another artist's fanbase.

Third, the reciprocal connections between individuals in a workplace setting can drive success because it creates solidary among groups and holds individuals accountable to others (Burt et al. 2022; Uzzi 1997). Chapter 6 applies this principle to the relationship that exists between an artist and the genre they are participating in. It operationalised the connection between the individual and the group in terms of the individuals' efforts to invest in or signal participation into the group, and the group's efforts to validate the participation of the individual. Chapter 6 presents a unique way to measure an individual-to-group reciprocity and finds that the extent to which an artist reciprocates or is reciprocated with by the group is associated with their structural position and career success. Structurally, those who receive more from the group than they send (those I call 'takers') are the most central and the least constrained by the group. As one would expect, this implies that those who are most desirable to the group (i.e. those who the group want to work with most) are the most prominent within the genre. But, unexpectedly, perhaps, they are the least constrained by the group. Despite being highly connected to the group, the connections that tie them to the group are nonredundant leaving them in a structurally competitive advantage. Their greater ability to bridge structural holes in the network through their low constraint could be a primary mechanism behind their desirability. It could be that they have access to nonredundant resources in the network because of the high degree of structural holes in *their* network (see Burt 1995; Burt 2004) which make them more valuable to the genre and therefore more desirable to work with. In other words, they may strategically position themselves to control the flow of valuable resources across groups within the genre and therefore be more desirable. The results further suggest that those who receive more than they send to the group have the most success (in this case streams) than those who are reciprocal or who give more than receive. These findings imply that the extent to which an individual signals their participation and is validated by the group influences their career success. However, those who are desirable to the group (i.e. those the group really want to work with) are those who are most prominent and successful.

Reciprocity to the genre, then, is less a driver of career success than the reciprocity that operates in other work settings (Burt et al. 2022; Uzzi 1997). Rather, this study highlights that that the benefits of collaboration on career success in music are, at least in part, driven through a delectate balance of relationships between an artist and their genre. Those who can successfully attract more incoming collaborations than outgoing is endowed by the genre as prominent, and this endowment translates to structural and career advantages.

One of the biggest takeaways from Chapter 6 is that it demonstrates the utility of a new theory and method for individual-to-group relations. However, it relates to the main goal of the dissertation because it shows how individuals in a group use collaborative ties to the group to signal their participation. This signal may be rewarded with a validating indegree reciprocal response from the group. The study then demonstrates that the extent to which an artist gives or takes from the group in terms of collaboration is associated with structurally advantageous network position and career success.

Contributions

This dissertation contributes to the academic scholarship on collaboration, networks, and music. Aiming to explore the mechanisms behind the relationship between career success and collaboration from a network perspective unlocked the logic of network theory, network topology, and embeddedness when exploring how people's relationships with others influence their own success. The extant literature on collaboration largely focusses on the ways in which working with others boosts the process of work or the quality of the end product through the exchange of resources among workers (Ali et al. 2021; Alsharo et al. 2017). Others focus on a network perspective whereby working with others generates bonds of affection (Yakubovic & Burg 2019) and accountability (Burt et al. 2022). This dissertation, however, joins a small but burgeoning literature that explores the network structure and the positions that individuals hold within that network (El Mezouar et al. 2019; Mora-Cantallops & Sicilia 2018; 2019). Across three empirical tests, this dissertation contributes to that literature by examining case-specific mechanisms such as the prominence and power of centrality, the reputation or resource reach of collaboration, and the signalling and validation of individuals-to-groups. The study successfully demonstrates the application of established mechanisms (like network position) to music. It excavates the role of centrality in an artist building popularity and success. It also draws out new theory from existing mechanisms like the nomination of indegree and outdegree centrality (Krackhardt 1987; Wasserman & Faust 1994) by operationalizing these terms into case-specific mechanisms of reputation, resource expansion, signalling, and validation. Applying themes like network embeddedness (Chapter 4), the resources associated with different types of collaborations on Spotify (Chapter 5) and the reciprocity of exchange (Chapter 6) broadens the field of research on collaboration and career success. Each study in this dissertation makes multiple contributions to the literature which as discussed in what follows.

Chapter 4 adds to the literature on collaboration, music, and networks. Borrowing the concept of embeddedness from economic sociologists, the study demonstrates that there is a network effect behind collaboration. Previous scholars on collaboration within music focus on how collaboration between artists augment the success of the produced song largely because the fanbases of both/all artists engage with it (Deshmane & Martínez-de-Albéniz 2023). The results from this study demonstrate that listeners are also conscious of which artists are central to the genre. That the structural position of artists related to other artists is associated with career success indicates that listeners are not just drawn to collaborated songs per se (Deshmane & Martínez-de-Albéniz 2023), but that they are conscious of the centrality of artists within a genre favouring the most prominent and influential. This finding demonstrates that rather than collaboration generating a reward between the artists like augmenting the final product (Ali et al. 2021; Alsharo et al. 2017) or building affinity between workers (Burt et al. 2022; Yakubovic & Burg 2019), but that it unlocks other benefits, at least in this context. Future researchers on collaboration networks may wish to explore this possibility beyond music. Examples could include whether centrality in collaborative networks influences the public opinion of organizations, their market share, or the popularity of world leaders.

Chapter 5 adds to literature that is aimed at exploring the many different contexts of collaboration and how collaboration operates in different settings across different occupations.

Across multiple other professions, scholars of collaboration find that teams work differently in different settings. From coders on GitHub (El Mezouar et al. 2019), to professional gamers (Mora-Cantallops & Sicilia 2018; 2019), to collaborators in a business setting (Cristea & Leonardi2019; Yang et al. 2022), the nature of collaboration and what benefits come from it are context specific. In this instance, borrowing logic from the network literature brings an interesting perspective to the context of streaming services and their role in facilitating collaboration. Although this study found only slight difference between the two types of collaborations, it provokes greater research into the functions of streaming services and the power of context when studying collaborations. Future scholars might consider studying other elements to Spotify like the relationship between collaboration and being added to playlist algorithms or how collaboration with other artists may unlock markets across the world for smaller artists.

Chapter 6 adds to the literature on exchange reciprocity (Holland & Leinhardt 1976), (Baldassarri 2015; Bearman 1997; Krackhardt 1987; Molm 2010; Molm et al. 2007), and group dynamics in collaborative settings (Burt et al. 2022; Cristea & Leonardi 2019). Foremost, this study extends the literature on reciprocity by changing the unit of analysis. Since Holland and Leinhardt (1976)'s original conception of the three types of balance between nodes in a network, scholars have developed measures of reciprocity that focus on the mutual connection between dyads in a group by examining the dyad or arc mutual connection (Baldassarri 2015; McMillan et al. 2022). These measures largely focus on a proportion of how many arcs in the network are mutual. Or on an individual level, how many ties that are sent from an ego to an alter are returned by the alter. Chapter 6 extends this by measuring an individual-to-group level reciprocal connection. It measures the sum of outdegree ties from an ego and then sums the indegree ties they receive from anyone in the group. By dividing the two it provides a ratio of reciprocity between the individual (the number of outdegrees they send) and the group (the number of indegrees the ego receives from any in the group). This ratio generates four substantively meaningful groups that are different from Holland and Leinhardt's (1976). If an ego has a ratio below one, they take more from the group than they give. If the ratio is above one, they give more than they take. While those with a ratio of one are perfectly reciprocal and reciprocated. Finally, those with no connections are isolated from the group.

The focus of an individual-to-group reciprocity adds to the literature on exchange and group dynamics. Specifically, it nuances the generalized exchanges that may occur within groups. Bearman's (1997) theme on reciprocal exchange demonstrates a chain of benefits is started when an ego sends to an alter. A sends to B and then B to C. If C then sends to A, the chain is complete, and the exchange can be deemed reciprocal in general terms. The current paper shift this into collaborative ties and theorises that an ego may signal to the whole group their willingness to participate by featuring on the work of alter. The group may then validate their participation by another member of the group (either the recipient or another member) featuring on the ego's work. Thus, in general terms, this exchange from ego to group is reciprocal. Conversely, the group may wish to nominate a desired participant and multiple members may feature on the desired ego's work. This group nomination is noted by those with ratios less than 1 (more in than out).

In sum, this dissertation contributes to many literatures that surround collaboration and networks. The aim of the dissertation is to explore potential mechanisms that drive the benefits of collaboration in music. Based on the methods and models used in this dissertation, future research could do more to untangle how collaboration influences career success in music and in other industries.

Future Research

There is a robust literature on the structural embeddedness and the role of network position predicting career outcomes (Burt 1995; Podolny & Barron 1997; Uzzi 1997). The models in Chapter 4 demonstrate the salience of over embeddedness (Uzzi 1997) and theorises that an over affiliation dilutes an individual's identity. Future scholars may wish to adopt a similar framework when exploring the identities and collaborative behaviours of individuals and organizations. In fields, like music where the identity and market position of an individual or organization is salient, the extent to which the organization operates alone vs. collaborates may have a similar effect as those observed in Chapter 4. For example, the diversification of product offerings in collaboration with other entities may blur the company's identity and confuse consumers (see Intribe).

There is a burgeoning focus on the rise of platforms and the role of platforms in shaping the way workers interact with each other (Criea & Leonardi 2019; Ravenelle 2017; Yang et al. 2022). Future researchers may leverage the case-specific mechanisms highlighted within Chapter 5 that demonstrate that platforms, in this case streaming services, facilitate different types of collaboration. The thrust of Chapter 5 being that the direction of collaboration influences different resources available to workers may apply across multiple industries. For example, in the production of knowledge within the academy, the direction of collaboration could be operationalised in terms of scholarly ownership. Scholars may wish to examine online repositories and applications like Google Scholar, ResearchGate and others and examine the success of authors in terms of their outgoing and incoming collaborative works.

Study 3 in Chapter 6 offers multiple opportunities for future research, especially within the networks and inequality literature. Considering the individual-to-group relationship in terms of signals, validation, and reciprocity offers a unique way to explore many social phenomena. For example, scholars interested in studying social closure or opportunity hoarding may wish to adopt this framework to explore how some individuals signal their participation but are not validated by their group. For example. exploring the demographic makeup of givers, takers and reciprocators in a work setting could be a method to explore the ways racial and gendered homophily influence the interactions between employees.

There are, however, some limitations to this dissertation. Mainly, the data that are used are very limited in scope and generalizability. First, the data only cover one genre of music and therefore any extrapolations from the studies about how collaboration operates can only be made to Grime. Similarly, since the sample drawn for these studies only includes verified Grime artists on Spotify the N size is very small. This means that there may be other statistically significant mechanisms behind the relationship between collaboration and career success that the models used across these studies did not observe due to the small cell sizes and degrees of freedom. Future scholars may wish to adopt a similar approach across the empirical studies but apply it to multiple genres of music or a more liberal sampling method (i.e. beyond Spotify artists). That the N size is different across the various success outcomes means that the models are not comparable. Researchers interested in comparing the effects of collaboration on different types of career success would have to restrict the models to the smallest N or impute on missing observations.

Furthermore, the data, although longitudinal, do not have many observation years. While the collaboration data used go back 22 years, the career success data are only from 2015 at the oldest. Any observations made from the models, therefore, need to be conservatively interpreted as, over more time, they may change. In line with this, the sparsity of the models means that there are a multitude of potentially interesting covariates to explore. Throughout the methodological stage of the dissertation balancing the degrees of freedom within each model with omitted variable bias meant that the models in the studies are parsimonious. Future studies with bigger datasets may wish to incorporate other variables like the number of genres an artist is associated with, their demographics, and their tenure. Each of these elements could influence their career success and potentially explain the effects of collaboration on career success observed in this dissertation.

The dissertation does not cover other aspects of connection between artists. This dissertation focuses on collaborations between artists as defined as featuring on each other's songs. There are, however, other types of collaborations and other types of connections that could exist between artists and influence their career success. Such types of collaborations could include production. The literature on intermediaries (Lizé 2016; Musgrave 2017) demonstrates that genre-adjacent actors like DJs have a strong influence over the success of artists and the ongoings of a genre. Furthermore, between artists there may be more than collaborative ties that may influence their success. For example, in Grime music there are many who share kinship ties (Target 2019), and many who have previously worked together in crews, pirate radio sets, etc. (Hancox 2019; Wiley 2017). Prominence in those networks could be associated with future career success. Thus, multi-modal and a multiplex approach to networks would better capture the myriad different ways that connectivity, embeddedness, and centrality as associated with career success in music.

Conclusion

In conclusion, this dissertation aimed to explore potential mechanisms driving the benefits of collaboration in music. Specifically, it leveraged data scraped from Spotify repository songsstats.com, alongside 22 years of hand coded collaboration data from Spotify to examine the role of network position, the resources accessed through different type of collaboration on Spotify, and the reciprocity of individual artists tot the group. The results from these studies suggest that collaboration with other artists benefits an individual artist by centring them within advantageous positions in the genre. Artists featuring on their work adds reputation and authenticity to their name while working on others' songs extends their fanbase. Finally, those who the genre deems most desirable (those who take more than they give) are more central to the group and have greater career success.

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APPENDICES

Appendix A: Full Table Testing the Nonlinearity of Degree Centrality Predicting Career Success

	Model 1 Streams	Model 2 Streams	Model 3 Popularity	Model 4 Popularity	Model 5 Monthly Listeners	Model 6 Monthly Listeners	Model 7 Followers	Model 8 Followers
Degree Centrality	0.06***	0.03+	0.31**	-0.01	0.06**	0.02	0.04*	0.03
	(0.01)	(0.02)	(0.10)	(0.08)	(0.02)	(0.02)	(0.02)	(0.02)
Degree Centrality * Degree Centrality	-0.00***	-0.00!	-0.01+	0.00	-0.00	0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year	0.14***	0.01	-0.59*	-1.08***	0.08*	-0.02	0.22***	0.17***
	(0.03)	(0.03)	(0.23)	(0.17)	(0.04)	(0.03)	(0.04)	(0.03)
Songs Total		0.01		0.04		-0.00		-0.00
		(0.01)		(0.03)		(0.01)		(0.01)
Playlist Reach (logged)		0.16***		4.13***		0.74***		0.38**
		(0.03)		(0.65)		(0.11)		(0.13)
Songs in Chart		0.06*		0.48*		-0.01		-0.03
		(0.02)		(0.24)		(0.03)		(0.03)
Constant	-271.69***	-13.09	1,244.87**	2,141.83***	-152.75+	32.70	-436.71***	-332.51***
	(51.26)	(57.22)	(472.67)	(345.33)	(84.49)	(66.40)	(81.89)	(65.03)
Observations	734	734	414	414	414	414	414	414
R-squared	0.20	0.32	0.11	0.33	0.09	0.27	0.17	0.21
Number of id	119	119	114	114	114	114	114	114

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p = 0.06 – 0.1

Appendix B: Full Table Testing the Nonlinearity of Betweenness Centrality Predicting Career Success

	Model 1 Streams	Model 2 Streams	Model 3 Popularity	Model 4 Popularity	Model 5 Monthly Listeners	Model 6 Monthly Listeners	Model 7 Followers	Model 8 Followers
Betweenness Centrality (Undirected)	0.00***	0.00	0.00***	0.00	0.00***	0.00+	0.00**	0.00+
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Betweenness * Betweenness	-0.00***	-0.00	-0.00**	-0.00	-0.00+	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Year	0.14***	0.01	-0.58*	-1.03***	0.09*	-0.01	0.22***	0.17***
	(0.03)	(0.03)	(0.23)	(0.17)	(0.04)	(0.03)	(0.04)	(0.03)
Songs Total		0.01*		0.04		0.00		-0.00
		(0.01)		(0.03)		(0.01)		(0.01)
Playlist Reach		0.16***		4.07***		0.73***		0.38**
		(0.03)		(0.67)		(0.12)		(0.14)
Songs in Chart		0.06*		0.47*		-0.00		-0.03
		(0.02)		(0.23)		(0.03)		(0.03)
Constant	-258.83***	-12.18	1,212.96*	2,052.78***	-155.33+	17.38	-436.08***	-339.99***
	(52.42)	(58.04)	(470.25)	(347.28)	(82.77)	(67.18)	(77.62)	(61.61)
Observations	733	733	413	413	413	413	413	413
R-squared	0.20	0.32	0.10	0.33	0.09	0.27	0.17	0.22
Number of id	119	119	114	114	114	114	114	114

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p = 0.06 – 0.1

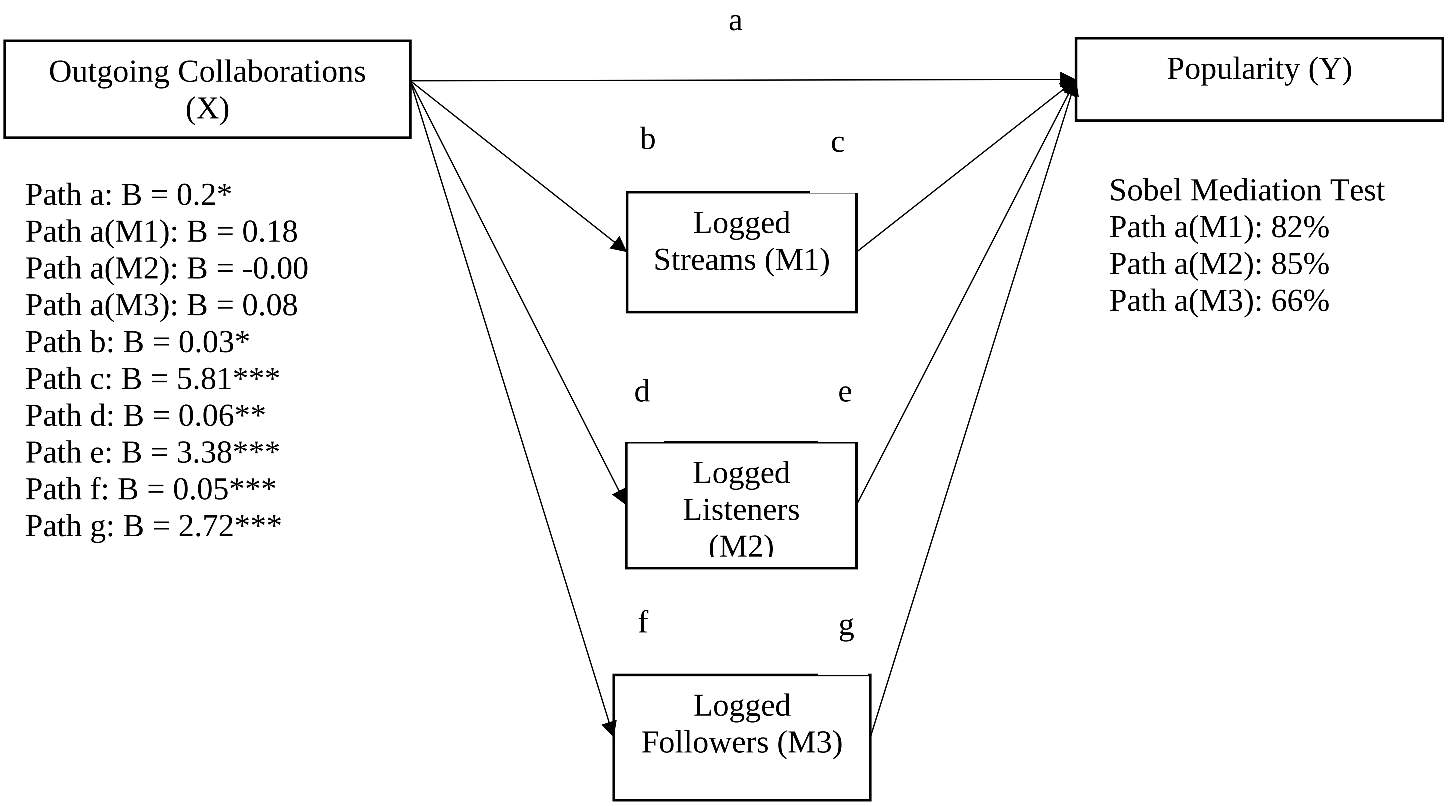
Appendix C: Full Table Testing the Nonlinearity of Eigenvector Centrality Predicting Career Success

	Model 1 Streams	Model 2 Streams	Model 3 Popularity	Model 4 Popularity	Model 5 Monthly Listeners	Model 6 Monthly Listeners	Model 7 Followers	Model 8 Followers
Eigenvector	1.42**	0.50	5.44+	1.24	0.79	0.21	0.73	0.49
	(0.44)	(0.43)	(3.19)	(2.42)	(0.75)	(0.70)	(0.67)	(0.69)
Eigenvector * Eigenvector	-1.39**	-0.69	-4.39	-0.91	-0.56	-0.08	-0.62	-0.41
	(0.47)	(0.43)	(3.23)	(2.12)	(0.82)	(0.66)	(0.73)	(0.66)
Year	0.15***	0.01	-0.62*	-1.05***	0.08+	-0.01	0.22***	0.17***
	(0.03)	(0.03)	(0.24)	(0.17)	(0.04)	(0.03)	(0.04)	(0.03)
Songs Total		0.01**		0.04		0.01		0.00
		(0.01)		(0.03)		(0.01)		(0.01)
Playlist Reach (logged)		0.16***		4.14***		0.77***		0.41**
		(0.03)		(0.65)		(0.11)		(0.13)
Songs in Chart		0.06*		0.48*		0.01		-0.02
		(0.02)		(0.23)		(0.03)		(0.03)
Constant	-292.28***	-13.83	1,292.97**	2,085.11***	-143.96	23.63	-434.70***	-338.62***
	(53.52)	(59.16)	(481.30)	(350.99)	(86.81)	(69.08)	(81.78)	(64.87)
Observations	734	734	414	414	414	414	414	414
R-squared	0.16	0.31	0.06	0.33	0.02	0.25	0.14	0.20
Number of id	119	119	114	114	114	114	114	114

Robust standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05, + p = 0.06 – 0.1

Appendix D: Mediation Models for Outgoing Collaborations and Artist Popularity



Appendix E: Mediation Models for Incoming Collaborations and Artist Popularity