Good Reverberations? Teacher Influence in Music Composition since 1450

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Teachers and mentors in creative fields shape their students' skills and views of the craft and thus the work they produce. How significant and persistent is this influence? Are there consequences for the variety and quality of students' inventive output? We study these questions in the context of Western music composition over five centuries, during which musical lineages are well documented, the content of composers' work can be directly compared, and its lasting value can be measured. We find strong evidence of influence, document when it arises and persists, and evaluate its consequences. The results provide insight into where creative ideas come from, why certain ideas get produced as opposed to others, and what the ramifications might be.

I. Introduction

Humans are a product of their environment, each a composite of countless influences accumulated over a lifetime. Teachers, in particular, can have a formative effect on the development of their students, one that

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has been documented in modern education vis-à-vis their effects on students' academic performance and later-life outcomes (e.g., Rockoff 2004; Rivkin et al. 2005; Chetty, Friedman, and Rockoff 2014a, 2014b) as well as historically (e.g., Waldinger 2010). However, a distinct—and distinctive—potential impact of teachers that is especially important in creative professions is their creative or intellectual influence: how teachers shape students' skills and views of the craft and, in turn, the nature of the work they go on to produce. Teachers or professional leaders with wide reach can potentially even affect the direction in which entire fields move.

Academic researchers may recognize the potential for this influence, reflecting on how they themselves may have been shaped by where they did graduate work, the faculty who taught their courses or advised them, and even their peers, evidence of which is casually observed in their disposition to different questions, methods, and applications (e.g., Margo 2018). On the one hand, instruction by subject-matter experts is essential for transmitting basic principles and skills and for the ability to discern good from low-quality work. But it may also imbue students with the tastes and methods of an instructor who is out of the mainstream or does not meet contemporary standards. At the extreme, this influence may even cause bad ideas to propagate. Whether or not teachers and mentors in creative fields leave an imprint on their students that shapes their future work is an empirical question. If the answer is yes, many questions follow, such as how extensive that imprint is, how long it lasts, whether some teachers have more influence than others, and whether there are consequences for the variety and quality of these students' inventive output.

In this paper, we examine these questions in the context of Western music composition over the span of about five centuries, from ca. 1450. Music composition is an attractive setting for studying these questions, for both phenomenological and practical reasons. First, composers were typically educated by other composers—in private lessons or conservatories, often locally, and at young ages—and this lineage is well documented in biographies and other reference works. Second, the content of musical

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compositions is relatively structured and can be mathematically compared to generate similarity measures on key dimensions for pairs of composers or individual works. Third, musicologist- and market-based measures of quality are available as well as data on the lives and works of important composers. Fourth, music education was widely available to broad parts of society in many countries throughout most of the time covered, and it was closely related to the teaching of composition. And finally, until the latter half of the twentieth century, the curriculum for music education was mainly determined by individual teachers or locally; only later came the standardization of curricula, instructional methodologies, and achievement standards.

To measure the similarity of two composers or musical compositions, we draw on data from two volumes (Barlow and Morgenstern 1975, 1976) that list 18,074 melodic themes from 6,352 classical works by over 750 composers. This source provides a list of themes in the form of lettered note sequences (conveniently transposed to a common key) as well as a staff for each theme showing the original key and time signatures. Though we acknowledge that this represents only a subset of the content of each work, it includes several of the most basic elements specified by the composer—with substantial variation across the sample—and we demonstrate that these observed dimensions of the works in our sample offer insight into the phenomenon, especially when viewed together. Using this information, we calculate similarity scores between pairs of composers and compositions on the observable dimensions of their work. Specifically, we measure similarity in the occurrence of subsequences of notes (duplets, triplets, quadruplets) in themes and overlap in the distribution of keys and time signatures of composition.

We combine these measures with biographical information on the composers in our sample: when and where they lived, the conservatories they attended, and their musical genealogy, including teachers and students, from *Grove Music Online* (2016–21; a modern update to the *New Grove Dictionary of Music and Musicians*, a leading reference work on Western music) and Pfitzinger (2017, a recent, first-of-its-kind volume listing the teachers and students of more than 17,000 composers). We then supplement these data with measures of composer quality obtained from three different independent sources. We measure the individual composer's distinction (from Murray 2003), the length of biographical entries in *Grove*, which correlates with importance, and modern consumption data (based on Spotify streams).

The composers in our sample are overwhelmingly (>85%) European, from all corners of the continent, and while some are household names today, many are less well known. The majority were born and educated in the eighteenth or nineteenth centuries, spanning the Classical and Romantic eras of Western music. Within the Barlow and Morgenstern (BM) sample, we have a few hundred educational relationships to other BM composers, of which most were established when the student was under 20 years old. The likelihood of any two composers being connected is strongly increasing in their geographic and temporal proximity but appears to be only weakly, if at all, related to their underlying ability, suggesting that sorting was primarily driven by the (exogenous) place and timing of each composer's birth, especially in an era when geographic mobility was limited.

The first challenge in studying the effects of these relationships is establishing a control group of unrealized candidate teacher-student pairs for comparison. We begin with the universe of all pairs of composers in our data and condition to pairs in which the older of the pair was alive for at least 1 year when the younger was between the ages of 5 and 30, labeling the older the "candidate teacher" and the younger the "candidate student" (among realized pairs, the teacher is always older than the student). This condition establishes a risk set of 28,546 candidate pairs, of which 211 were in fact realized. Our first set of tests compares the similarity of realized pairs against that of unrealized pairs, conditional on various fixed effects and flexibly controlling for the two composers' birth distance in space and time, which may jointly affect the similarity of their work and the likelihood of connection. In a range of robustness checks, we explore variants of this specification and sampling condition, such as restricting to European-only pairs or comparing similarities across composers located in the same city at the same time.

We find that students are, on average, roughly 0.2–0.3 standard deviations more similar to their realized teachers than to other, unrealized, candidate teachers.

A potential threat to the empirical approach is that composers may have chosen to teach or to study with a particular composer on the basis of their style. This is a fairly unlikely concern in this historical setting and context, since composers typically began lessons with their teachers at an early age and—according to our data—had almost never composed anything before meeting their teachers. Furthermore, information exchange and the possibility of travel were fairly limited in the time periods covered. Nonetheless, we pursue several additional and robustness approaches to mitigate the concerns, including within-conservatory natural experiments, which exploit teacher turnover at music conservatories and compare a student's similarity to his actual teacher at a given conservatory with that to candidate teachers who had recently departed from or had not yet arrived at that particular conservatory.[1] We also study influence at the composition level and demonstrate that the student's style after the initial training is more similar to the teacher's style from before it,

[1] As the study encompasses only male composers, the male form is used.

but that the similarity subsides with time. We then show that influence persists through the next generation in a composer's musical lineage, as many students went on to become composition teachers themselves, but that the effect subsequently starts to fade. Finally, we study horizontal similarity and disclose that students who had a teacher in common were more similar to each other than to other, unconnected composers. All these approaches consistently and collectively point to the importance of the teacher in the shaping of a student's style of work.

We then explore the conditions under which the influence arises. This effect is relatively stronger for higher-quality teachers or for those who invest more time in the student but does not seem to vary much depending on the student's subsequent career; put in another way, the student, once exposed to the teacher's influence, appears to have limited possibilities to depart from it in ways other than through the passage of time.

Next, we evaluate the consequences of this influence and show that students who imitate high-quality teachers are themselves more likely to become higher-quality composers. On the other hand, imitation of teachers in the bottom quality quartile may have reduced students' chances of success later in life.

Finally, we assess how competition between composers matters for the extent of a teacher's influence and the novelty of compositions. The degree of competition is approximated with the number of other composers located in the same city at the same time. The results are suggestive of a lower similarity across composers who are exposed to higher competition. In other words, those who are located in cities with many other composers appear to have a more distinct style.

The results have implications for economists' understanding of the production of creative or intellectual output, specifically around questions of where ideas come from; why certain ideas get produced, as opposed to others, and by whom; and what the consequences might be—questions that are of general interest and may be especially important to modern growth theory, the economics of innovation, and cultural economics.

The paper is organized as follows. Section II presents the relevant literature. Section III summarizes the historical context. Section IV describes the data sources. Section V provides the estimation framework. Section VI shows the effects of connection on similarity. Section VII outlines the conditions for influence. Section VIII shows the implications for composer's quality. Section IX presents the role of competition. Section X concludes the paper.

II. Literature

To place our study in context, we use this section to summarize existing research on the creative process, innovation in history, teacher influence, cultural transmission, and musicians and music.

A. *The Creative Process*

The creative process depends on the knowledge of a creator. The two ways in which this knowledge emerges are formalized by Akcigit et al. (2018). First, knowledge is created from interaction with other people, and second, it stems from external sources related to one's own explorations over time. It is especially the former channel that is fundamental to our paper, albeit the latter one—the age-dependent factor—is also explored here. With a focus on person-to-person transmission of tacit knowledge, de la Croix, Doepke, and Mokyr (2018) show that the transmission of knowledge in master-student relationships was more important for technological creativity than transmission within extended families or clans in preindustrial Europe. Instead, the underlying paper studies the person-to-person transmission of creative style.

Another approach to modeling the creative process is provided by Feinstein (2011): creators explore and gather elements before finding ways to combine and reconfigure these elements into new creative forms. Teacher-student interactions may thus shape the creative process by directing the student toward elements that are familiar to the teacher.

B. *Innovation in History*

Creativity thrives in environments where individuals are free to pursue their own paths of inquiry and creative expansion (Simonton 2004; Feinstein 2006; Aghion, Dewatripont, and Stein 2008). A culture of growth connected with interhuman interaction sparks innovation (Mokyr 2016). Innovators play an important role, not only by creating but also by actively influencing others as they spread their improving mentality (Howes 2017).

Our study is also motivated by the literature on upper-tail human capital and economic development (Mokyr 2009; Meisenzahl and Mokyr 2011; Squicciarini and Voigtländer 2015) or the growth literature, which defines economic growth as a function of the generation and transmission of new ideas (e.g., Jones 2005; Lucas 2008). These strands build on the notion that ideas are transmitted across individuals and that (creative) people are able to influence each other. However, so far direct evidence on how this transmission from person to person occurs is very limited. This is not surprising, given how elusive the concept of an idea is.

Several authors have mapped and quantified creative activity over time and place. Murray (2003) selects and ranks leading innovators in the arts and sciences from 800 BC to 1950. Gergaud, Laouenan, and Wasmer (2016) document the geographic expansion of talented individuals and creative clusters. In such clusters, human interaction increases the innovativeness of visual artists (Hellmanzik 2010) and music composers (Borowiecki 2013, 2015a).

C. *Teacher Influence*

The literature on how teachers influence students deals with students' academic performance and later-life outcomes (e.g., Rockoff 2004; Rivkin et al. 2005; Chetty, Friedman, and Rockoff 2014a, 2014b; Jackson, Rockoff, and Staiger 2014). One of the more prominent works in a historical context is provided by Waldinger (2010), who explores whether the quality of a teacher matters for the future performance of a PhD student. The dismissal of Jewish professors in Nazi Germany is used as a source of exogenous variation, which allows the author to conclude that faculty quality is an important determinant of short- and long-run PhD student outcomes. Azoulay, Stuart, and Liu (2017) explore the influence of advisers on young scientists, who are shown to adopt their advisers' orientations toward commercial science. Others approach teacher-student relationships from a network perspective. For example, Tol (2018) constructs a professor-student network of Nobel laureates in economics.

The learning and teaching of musical composition plays a central role in musicology (see Viig 2015 for a review). The long-lasting influence of composition teachers is common knowledge, as "music teachers enjoy an almost genealogical immortality through their students" and "teachers imprint their students with the specific physical traits of their craft: gestures, tics and preferences that those students may in turn pass on to yet another generation." All this allows teachers to "exist as sound" (da Fonseca-Wollheim 2017) in the future work of their students. However, systematic, quantitative evidence in support of such claims is missing.

D. *Cultural Transmission*

Bisin and Verdier (2011, 340) define culture as something representing those components of preferences, social norms, and ideological attitudes that "depend upon the capacity for learning and transmitting knowledge to succeeding generations." Children acquire preferences through adaptation and imitation of a parent as well as role models such as teachers (Bisin and Verdier 2001).[2] The exposure to ideas and influence of certain teachers may shape a person's norms and preferences (Bordo and Istrefi 2018).

Our analysis relates to this literature by providing insights into the transmission of knowledge to succeeding student generations. Furthermore, although not yet explicitly studied, the transmitted preferences

[2] See also early applied work in psychology on the extent and mechanisms of intergenerational transfer of personality traits (Simonton 1983) and intergenerational influence (Simonton 1984a).

may also be directed toward a creative product of a certain type.[3] Acquired taste determines, for instance, why some find delight in contemporary art while others detest it or—in the context of our study—why certain composers compose what they do.

E. Musicians and Music

The lives and works of famous music composers have been studied in various contexts and across several disciplines, perhaps in reflection of the importance of the institution of music in history (e.g., Bonds 2006) or as an acknowledgment of the contribution musicians have made to the cultural heritage. Psychologists—most prominently Dean K. Simonton—have explored musical structure and whether it can reveal the psychology of musical aesthetics and creativity (e.g., Simonton 1980, 1984b). Musicologists explore the structure of musical works in order to categorize them (e.g., Serrà et al. 2012), explore how they changed over time (e.g., Foster, Mauch, and Dixon 2014), or analyze their role in the evolution of popular taste (Mauch et al. 2015). Styles of individual musicians have also been explored (e.g., Smith and Georges 2014). These studies typically emphasize musical characteristics of one or a few individual composers but typically do not explore how a composer's background or the environment matters for the development of a particular style.

III. Historical Context: Music Education and Originality in Music

It is beyond the scope of this section to present a detailed account of the music history context, but in what follows we sketch out the key developments in music that are most relevant to this paper. In doing so, we focus on music education and how it has changed over time as well as on the perception of originality in music.

In medieval Europe, the tradition of music education was based at monasteries, cathedrals, and parish schools.[4] It often began at young ages, as was the case with our earliest composer—Josquin des Prez, born in 1450—who was taught singing as a choirboy at a church. Later, he may have studied counterpoint under a lesser-known composer, who is not

[3] Our validity tests also shed some light on how acquired taste depends on the country of birth (see app. D3): composers born in the same country compose more similar works than composers born in different countries.

[4] This is the first, but not the last, mention of religious institutions in this section. The reader may thus expect that the role of religious denomination is more closely discussed and examined. We pursue this in app. D4.

covered in this study. Coinciding with des Prez's lifetime, the five-line staff became more widely used, and hence music could be written as it was to be performed. This was an important development that enabled composers to write music and increased the value of the ability to read and write music. As a result, notation became a major subject of study, and the better students continued to study composition (Mark 2008). The popularity of music education contributed to a further development of the methods of writing music and later brought along the detailed notation of Renaissance polyphony.

Teaching of singing and instrumental music was advocated and facilitated further by Protestant reformers. Consequently, the curricula in the newly established schools included formal music education from as early as the seventeenth century. Students at the elementary level studied music principles, while those at the intermediate level progressed to music theory and composed music in class (Livingston 1971).

Along with the rising popularity of composition, theoretical considerations emerged about what constitutes the composing of music. The French composer Jean-Benjamin de Laborde (not covered in this study) proposed in 1780 that "composition consists . . . [of] the ordering and disposing of several sounds in such a manner that their succession pleases the ear. This is what the Ancients called melody" (Laborde 1780, 2:12). This definition has been regarded as accurate throughout most of history (Forte 1979), and it is also clearly reflected in the methodological approach of this paper.

The Protestant model of music education was successful not only in revealing the most talented students, who proceeded to receive individual tuition, but also by influencing schools abroad, including, for example, those in nineteenth-century America (Mark 2008). The nineteenth century, a golden age for classical music, was also an important period for music education, with its formalization and secularization in the newly founded conservatories across the world. The earliest conservatories had been in existence in Naples since the sixteenth century, but it was not until the turn of the nineteenth century that conservatories were founded in most of European cities, and later also in the Americas.

Throughout the centuries covered in this study, instructional methodologies were largely determined by the music teacher. It was also usually the individual teacher who locally determined the curriculum for music education. This began to change in the second half of the twentieth century with the onset of standardization in music education, especially with regard to recently developed instructional methods, which were disseminated more widely (Costanza and Russel 2017). Perhaps not surprisingly, several composers played important roles in advancing instructional methods of music teaching, including Zoltán Kodály, Carl Orff, and Émile Jaques-Dalcroze. It was also in the latter half of the twentieth century that assessment standards were developed and introduced. The use of standards provided guidance on the performance of teachers and had become a common practice in most countries by the late twentieth century (Abril and Gault 2016). Assessment standards typically included criteria related to composing and arranging music within specified guidelines.

Another important development in music relates to the perceived value of originality. Until the eighteenth century, music was composed for a particular occasion. Once performed it was often not used again. Therefore, composers would regularly rewrite their own music in order to accommodate a new circumstance or audience. Similarly, music by others was often appropriated for reuse, and such borrowing would not raise any concerns of plagiarism. Originality became increasingly praised from the mid–eighteenth century and eventually became regarded as superior to imitation (Burkholder 2001). In consequence, the quality of a composer was increasingly assessed by the inventiveness of new music, as opposed to skillful manipulation of existing material.

Alongside these cultural shifts, several other developments shaped the nature and value of music making. First of all, there emerged a popular interest in music, reflected in the demand for sheet music and music teaching for the offspring of the rising middle class. Public performances gained popular appeal and were staged in newly built concert halls and opera houses across European cities. The standing of a composer was promoted from artisan to artist, while music became an art form, exercised for its own sake.

These changes created an unprecedented array of opportunities for music composers and enabled them to seek employment on their own, as opposed to remaining dependent on their patrons. Wolfgang Amadeus Mozart, born in 1756, has been suggested as one of the first entrepreneurial composers who was able to compose what he wanted and supply his services as he pleased (Scherer 2004). This was possible after Mozart parted from his patron Archbishop Colloredo, having received a notorious "kick in the butt."

Self-promotion and branding of one's own name became important for the composer, as this enabled the artist to distinguish himself from others. This also raised the interest in the composer as a person and led to more careful ascription of ownership of a musical work. As a result, originality grew in importance. Borrowing remained acceptable, but existing music had to be placed in a new, different context. Existing work, especially musical classics but also less prominent earlier work, was emulated by composers in their education and training. However, it has became increasingly recognized that "only sly allusion, like a wink to the connoisseur, or addressing the same musical issues in a new and original way could allow the younger composer to reach a level equal with his predecessors" (Burkholder 2001, 44).

IV. Data

We draw information from several databases, including dictionaries of musical themes, encyclopedias of music and musicians, and modern music consumption data. This section describes these data sources and the pursued approaches to estimation, but first we provide some details on the data collection process.

A. Data Collection Process

The data collection was conducted in a planned, structured, and systematic way. As outlined below, the process relied on a large number of motivated research assistants, mostly with training and interest in music; involved continuous and independent checks, often supported by computer-based algorithms; and included regular consultation and dialogue with experts, especially musicologists and musicians, including composers.

The quality of the manual data collection efforts was ensured in a number of ways. First, regular contact with individual research assistants and meetings in groups ensured correctness, consistency, and a high intrinsic motivation across the team. Second, the author of this study and Daniel P. Gross extensively and randomly checked entries throughout the whole process. Third, we conducted double checks by asking another research assistant to independently collect the same part of the data, and then we studied any discrepancies. Fourth, whenever possible we triple-checked entries, using automatically scraped data from *Grove Music Online* covering standardized variables (e.g., date and country of birth). All these efforts diminish the risks of any systematic errors in the data collection process and ensure that data entry errors such as typos are largely eliminated.

Wherever possible and appropriate, we collected control data from additional and independent sources. For example, we obtained four composer-quality metrics from three independent sources. Furthermore, we coded data in different ways to ensure that results were not driven by any of our potentially subjective choices. For instance, our baseline results are for eight different (albeit correlated) measures of similarity between pairs of composers or compositions. Finally, we conducted a range of robustness tests (see app. D2) and validity tests (see app. D3).

During the planning phase of this project and as it progressed, input from experts on music, music history, and music education was continuously and consistently sought and was incorporated whenever possible, including from musicologists (e.g., at the Harvard University Department of Music or the Department of Music at the University of California Santa Barbara), music librarians (e.g., at Trinity College Dublin), composers (e.g., Scott Pfitzinger, who is also an expert on teacher-student relationships), and a number of amateur and professional musicians, mostly from personal networks.

The data collection process was planned during the summer and fall of 2014; it began in October 2014 and lasted until early 2018. The databases have been extended in various ways over the period from December 2020 to April 2021, during revisions. The collection of data was supported by a total of 13 research assistants, who are listed in the acknowledgments. Those who were supporting the collection and processing of musical content were required to have musical training. In total, eight of the research assistants had degrees or were studying for degrees in music (sometimes dual degrees in music and economics). Some of our assistants were affiliated with the Harvard University Department of Music; others worked as freelance musicians. Each one had a keen interest in music or music history and is acknowledged as a crucial contributor to the outcome of this project.

B. Musical Themes

We collect data on musical themes from two volumes of the extensive *Dictionary of Musical Themes* by Barlow and Morgenstern (1975, 1976). The data contain information on 18,074 melodic themes from 6,352 classical works by 769 composers. We digitize more than 1,200 pages that list themes from individual compositions, showing lettered note sequences, staff, key signature, and time signature (see fig. A1 for a sample theme). All themes are transposed to a common key of C (major/minor), which enables standardized comparisons. The note sequences vary in length and contain between three and 15 notes. As a baseline, we consider all provided notes. However, we conduct robustness tests by truncating the note sequences and consider instead only the first six notes of a theme (>99.8% themes contain at least six notes). We complement this with manually collected information on the original key and time signatures. A key signature indicates notes that are to be played higher or lower than the corresponding natural notes (see app. C1 for details on how we identify key signatures). Time signatures specify how many beats are to be contained in each measure (segment of time) and which note value is equivalent to one beat. The information available for each theme represents only a subset of the content of each work; however, it includes several of the most important characteristics of a music composition specified by the composer.[5] This permits us a unique possibility to quantify some of the main characteristics of a creative product and to measure the similarity between compositions and pairs of composers.

[5] Melody (linear succession of musical notes) and tonality (key signature) are key features of classical music that enable listeners, among others, to identify the historical period or the composer of a work (Weiss, Mauch, and Dixon 2014).

Similarity is calculated in several different ways using *N*-gram–based measures, where an *N*-gram is defined as a group of *N* consecutive notes (e.g., duplet, triplet, quadruplet), as well as cosine similarity measures of key signature and time signature distributions. We begin by estimating similarity coefficients for pairs of composers by compiling all of the *N*-grams, key signatures, and time signatures for each composer into a corpus. This information is then used to, first, calculate the Jaccard index, which is given by the percentage of collective *n*-grams shared by a pair of composers: $|T_{1n} \cap T_{2n}|/|T_{1n} \cup T_{2n}|$, where $N = n$, and T_{in} represents the sets of *n*-grams in themes by composer *i*. Second, we calculate the cosine similarity of the *N*-gram distribution: $(P_{1n} \cdot P_{2n})/(\| P_{1n} \| \ \| P_{2n} \|)$, where P_{in} is the probability mass function of *n*-grams by composer *i*. Third and fourth, we calculate the cosine similarity of distribution of common key signatures and time signatures, respectively. Table B1 shows the similarity measures for BM composer pairs.

We complement the composer-pair level approach with an analysis of similarity at the composition level. In analogy, we calculate similarity coefficients for pairs of compositions by considering the percentage of collective *n*-grams shared by two compositions and the cosine similarity of the distributions of *n*-grams, key signature, and time signature of two compositions. The composition-level approach could potentially permit us insights into the timing of a teacher's influence but requires knowledge of the years when a work was composed. Therefore, we collect the composition year for all works that we are able to match with the corpus found in the International Music Score Library Project (IMSLP 2016–19; see app. C2). Unfortunately, this information is limited, which will constrain to some degree the composition-level explorations. Finally, we identify for which instrument or instruments each work is composed, and we obtain information on the musical form of each composition. These records are provided for the majority of works in Barlow and Morgenstern (1975, 1976; see app. E5).

C. *Composer and Composition Data*

Data on music composers is collected from the *New Grove Dictionary of Music and Musicians* (*Grove*), the leading encyclopedia for musicology offering comprehensive coverage of music and musicians. The data cover 341 composers who have at least five themes listed in the BM dictionary.[6] We have

[6] This covers approximately half of the composers listed by Barlow and Morgenstern (1975, 1976) and includes 94.5% of all the themes. In robustness tests, we confirm, with more rudimentary, automatically collected data, that the main results presented in this study would not be different if instead all 769 BM composers were used.

collected information on the birth and death years, birth city, and cities visited over the lifetime of composers, along with the approximate years and reasons for the move. Most of the biographical records from *Grove* were collected manually. This was necessary because of the complex and irregular structure of the information provided. Collecting data for 341 composers lasted, in total, 445.8 hours.[7] Parallel to this, we used self-developed computer software to scrape all systematically available data from *Grove* (e.g., birth and death dates and places).

Figure A2 shows the distribution of composers' birth locations. The map illustrates the concentration of music activity in Western Europe and the United States. There is, however, a large variation in locations in these two regions, especially across Europe (see fig. A3). Table B2 presents the distribution of composers by century of birth.

The data also contain a list of conservatory affiliations, including an indication of whether the composer was a student or faculty and approximate dates of enrollment or employment. We also obtained for each composer a detailed list of teachers and students, along with an indication of how they met. Knowing the teacher-student relationship is crucial for our analysis. It is thus encouraging that this information is relatively well preserved and reliable. This is due to the prominent role played by a composition teacher in a composer's life and career, where being part of the lineage of a particular musician is often used to help establish one's own credentials, even more so than, for example, in science. Given this importance, Pfitzinger (2017) has dedicated much of his career to listing teachers and students of 17,460 composers in the extensive volume *Composer Genealogies: A Compendium of Composers, Their Teachers, and Their Students.*[8] Combining all connections from *Grove* and Pfitzinger (2017) delivers 211 connections for the BM sample of composers. Table 1 shows the distribution of BM composers by the number of teachers and students also included in the BM dictionaries.

It is important to remark that composers typically began lessons with their teachers at very early ages. The mean age is about 18 years, and 75% of composers met their teachers before the age of 22 (see table B3). Moreover, the first meeting with a teacher nearly always (>96% of pairs) took place before the student began composing.[9] In other words, the subjects of our study were typically connected with composition teachers

[7] This gives an average time per entry of 76.4 minutes, with a maximum of 315 minutes spent on a 24,370-word-long biography of Franz Liszt. In exploratory data-quality tests, we have monitored and studied the time used by the research assistant per entry in relation to the word-count length of the biographical entry.

[8] We assess and discuss the reliability of this source in app. D5. There we also explore the potential difference between the influence of a composition teacher and that of a teacher of instrumental music.

[9] This is estimated for student-teacher pairs for which we have the year of their first meeting and the year of composition for at least one of the students' works in our data.

TABLE 1
Distribution of BM Composers by Number of Teachers and Students

	Teachers		Students	
	Number	Percent	Number	Percent
0	193	56.0	244	71.6
1	96	28.2	57	16.7
2	37	10.9	16	4.7
3	13	3.8	9	2.6
4	2	.6	4	1.2
5+	0	0	11	3.2
Total	341	100.0	341	100.0

Note.—The table reports the number of teachers of a student and the number of students of a teacher. Connections are counted only if both student and teacher were listed in Barlow and Morgenstern (1975, 1976). The data were collected by the authors (see sec. IV for details).

before they became composers. This mitigates to some degree the concern regarding self-selection based on a particular style of composition.

D. *Quality Measures*

To evaluate the quality of a composer, we collect four different metrics from three independent sources. In particular, we obtain expert-based measures, which enable us to rank composers or quantify their importance on the basis of what and how much musicologists have written about each composer. Furthermore, we compute market-based measures from modern consumption data.

First, we obtain an achievement index from Murray (2003), who ranks leaders in several fields of human accomplishment, including Western music. The achievement index reflects the coverage a composer receives in a large number of international reference works, which is useful because it mitigates the concern of country-specific biases and, hence, has often been used interdisciplinarily in studies of creativity (see Simonton 2004). Murray's procedure is well established in historiometric scholarship, and the reliability of the indices is "favorably comparable with the best seen" (Simonton 2014, 55). The index is normalized on a scale from 1 (lowest) to 100 (highest) and covers 189 composers from the BM sample. To those who have not been prominent enough to be included by Murray we assign an index equal to zero.

Second, from *Grove* we automatically extract word-count measures from different sections of a composer's biography—that is, life, works, bibliography, and writings. The word count in the life section is a commonly used measure of the importance of a historical figure and correlates particularly closely with the length of entries in the works and bibliography sections.

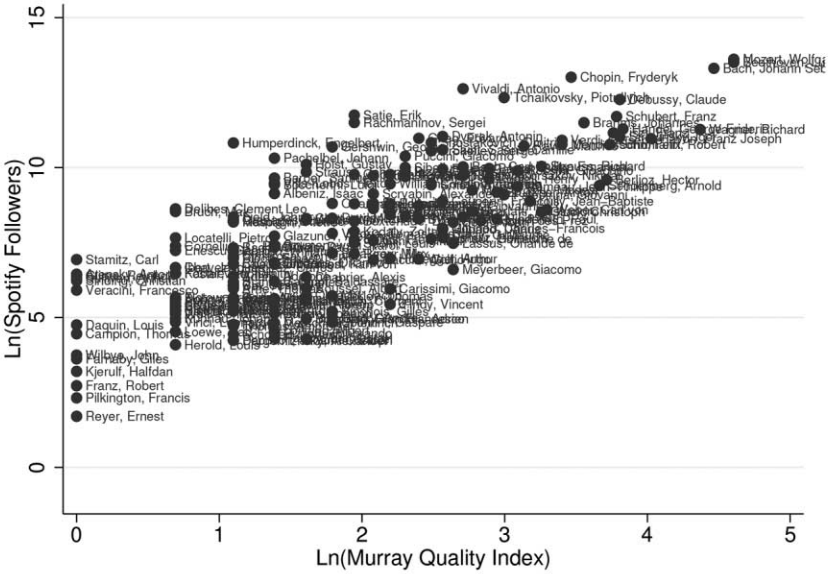

Fig. 1.—Spotify followers versus Murray quality index. The scatterplot presents the relationship between the logged number of Spotify followers (ln(Spotify Followers)) and the logged Murray quality index (ln(Murray Quality Index)). The data were collected by the authors (see sec. IV for details). A color version of this figure is available online.

Third, we use modern consumption data based on Spotify streams. For each composer we retrieve the total number of Spotify followers and a proprietary popularity score (measured on a scale from 0 to 100). Some music may be seasonal, and hence the collection took place over a 12-month period from October 2016 to September 2017 and was then averaged out. The positive correlation between Spotify followers and popularity score is reported in figure A4.

Figure 1 plots the correlation between logged Spotify followers and the logged Murray quality index. It is clear that composers with a greater coverage in historical reference works are also more often listened to nowadays. It is unsurprising that composers such as Ludwig van Beethoven, Wolfgang Amadeus Mozart, and Johann Sebastian Bach are in the top-right corner, followed by many household names and ending at the bottom left with somewhat lesser-known composers (see fig. A5 for similar positive patterns among the other quality measures).

A recurring concern in the literature on teacher's value added is self-selection based on quality: better teachers tend to select better students, and vice versa. Therefore, a relevant concern is the quality of connected

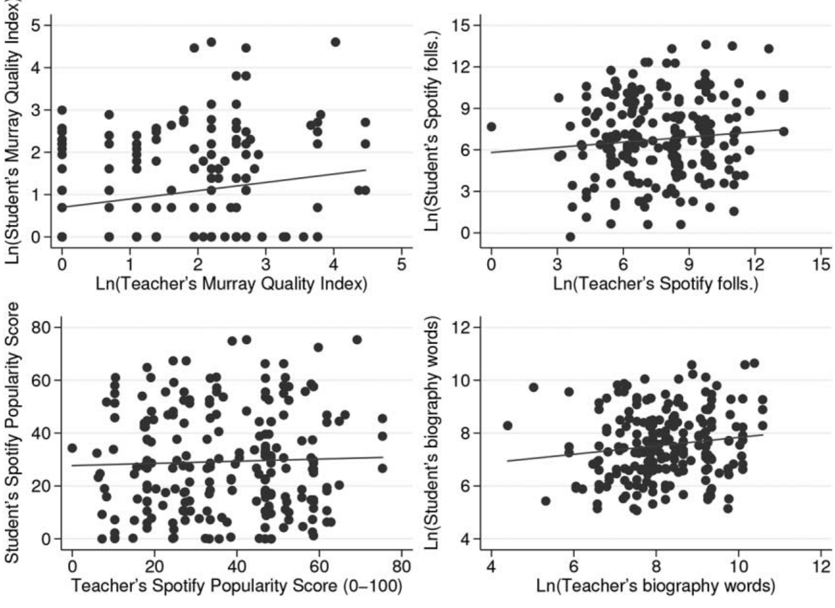

FIG. 2.—Connected: teacher quality versus student quality. The scatterplots show that there has not been a clear relationship between the quality of a teacher (horizontal axis) and that of a student (vertical axis) when using four different quality measures, as follows: the logged Murray quality index (*top left*), the logged number of Spotify followers (folls.; *top right*), the Spotify popularity score (0–100, *bottom left*), and biography word count (*bottom right*). The data were collected by the authors (see sec. IV for details). A color version of this figure is available online.

teachers and students.[10] Figure 2 shows scatterplots using our four quality variables for connected pairs. Interestingly, the relationship appears insignificant: good teachers were teaching both better and worse students, and worse teachers also had both better and worse students. This suggests, for our sample, that students and teachers were not connecting on the basis of considerations about quality. Above, we also observed that matching was unlikely to be based on composition style, since students had almost never composed anything before connecting with a teacher. The connections may thus have been created on the basis of other characteristics, possibly related to chance. After all, in the historical period covered, information was relatively scarce and traveling difficult. Random-like matching may have been inefficient for the composers studied but becomes useful for our identification strategy.

[10] Scherer (2004) invited "more systematic statistical research" into the question of whether "youngsters exhibiting talent are attracted to and attract talented teachers." In this sense, fig. 2 provides the requested test.

V. A Framework to Study Influence

This section proposes a simple framework to study influence, which is followed by a presentation of the empirical setup.

A. *Style*

We begin by defining the style of a creative person and by conceptualizing what determines it. Most broadly, style is a manner or custom of behaving or conducting oneself. Therefore, the concept of style is of general interest and has been studied in recent years in various contexts, including in economics (e.g., leadership styles, by Bertrand and Shoar 2003) and management science (e.g., styles in product design, by Chan, Mihm, and Sosa 2018).

A narrower definition suggests that style is a particular manner or technique by which something is created, written, or performed. It is a distinctive characteristic of a person, group of people, place, or period. Accordingly, style plays a particular role in the creative industries because it permits the grouping of creative output or the producers thereof into categories. Thus, the classification of style can be useful in the study of, among others, architecture, advertising, publishing, video games, or the arts, including music.

A creative output has to contain at least some unique attributes (otherwise it would be a replication and not creative), but the remaining attributes may resemble those of existing outputs. On the basis of this resemblance, it is possible to classify creative output into a certain category of style. The style can be captured as a function of key attributes. For example, in architecture such attributes may include the shape of a building, a method of construction, or building materials. On the other hand, classical music style attributes may include specific sequences of notes or a particular key and time signature.

We propose that style is a function of indirect and direct influences:

$$\text{Style} = f(\text{indirect influences, direct influences}). \tag{1}$$

Indirect influences are external factors, the zeitgeist, or something "in the air," and such influences are a function of the place where and time when a creative was born and the interaction of the two. Direct influences depend on individuals whom the creative person learns from or interacts with. The framework could be used to study the influence of any single individual or group of people who may have influenced the creative person. However, a particularly formative effect on the development of a creative stems from the interaction with a teacher, which is also the focus here. Conditional on two individuals being connected as teacher and student, the extent of the direct influence of an educator will be a product of the teacher's investment of time in the student and the student's subsequent career—the time dedicated to compose as well as exposure to other influences.

B. Estimation Strategy

Building on the theoretical considerations presented above, we proceed to an empirical measurement of similarity. Considering what determines style, as seen in equation (1), we construct similarity measures between two creatives i and j. This results in similarity measures that are a function of differences in the indirect influences, which can be captured via pairwise overlap in time and place, and direct influences, which can be determined on the basis of indicators showing whether a pair has been connected or not.

With a focus on music composers, we estimate similarity measures between composers i and j by using variants of the following specification:

$$\begin{aligned}\text{Similarity}_{ij} = \gamma_0 &+ \gamma_1 \times \text{Connected}_{ij} + \gamma_2 \\ &\times \ln(\text{Geographic birth distance})_{ij} \\ &+ \gamma_3 \times \ln(\text{Temporal birth distance})_{ij} \\ &+ \gamma_4 \times \textbf{Commonality controls}_{ij} \\ &+ \text{ComposerFE}_{ij} + e_{ij},\end{aligned} \tag{2}$$

where Similarity$_{ij}$ measures the percentage of collective n-grams shared or the cosine similarity of n-grams, key, and time signature for a given pair of composers, i and j; Connected$_{ij}$ is an indicator of connected pairs, ln(Geographic birth distance)$_{ij}$ is the logged geographic distance between birthplaces measured in kilometers, and ln(Temporal birth distance)$_{ij}$ is the logged temporal distance between birthplaces measured in years. The vector **Commonality controls**$_{ij}$ is a vector of dummies for common birth country, common time period measured in 25-year intervals, and their interaction; common nationality; and common family. Composer fixed effects (ComposerFE$_{ij}$) control for time-invariant differences across teachers.

We condition to pairs of composers (connected or not) in which the older of the two composers in a pair was alive for at least 1 year while the younger was between the ages of 5 and 30. The condition holds for all connected composers and ensures that the older composer in the pair (*candidate teacher*) could have met the younger (*candidate student*). Implicitly, comparing only contemporaneous composers leads to the mitigation of time-related differences, including, for example, changes in compositional style. In appendix D1, we explore a number of alternative conditions that restrict our samples to the same time period and geographic proximity in several different ways, including a highly restrictive condition that requires realized/unrealized pairs to be located in the same city at the same time. The results that follow hold for all the variants of conditions pursued.

A concern may relate to nonrandom matching, which could be an issue if students (or teachers) self-selected into relationships on the basis of styles of their output.[11] Ideally, the degree of similarity was measured before and after the student was exposed to the influence of the teacher (see sec. VI.C). Alternatively, one could exploit random-like incidence of connecting (see sec. VI.B). Of interest is also the consideration of the intensity of creative influence, which may differ, depending on the teacher's effort and skill and the student's subsequent career (see sec. VII).[12]

VI. Effects of Connection on Similarity

A. *Connection and Similarity: Baseline Results*

The starting point of our empirical investigation is a comparison of the similarity between a student composer and his actual teacher (realized pair) and that between the student and his candidate teachers, that is, composers who were alive during the student's formation age but were not connected (unrealized pairs).[13] Table 2 summarizes the results based on equation (2) in eight regressions—one for each of our measures of similarity: percentage of collective 2-/3-/4-grams shared and cosine similarity of 2-/3-/4-grams, key signature, and time signature. Each regression includes a set of commonality controls to identify pairs that share birth country, time period (and their interaction), nationality, and descent.

All point estimates for Connected are positive and estimated with high precision. Connected composers are more similar to each other than to unconnected composers by about 0.1–0.3 standard deviations. It is encouraging to observe that the size of the effect is comparable across all our measures.

Considering the importance of cities for music composition, one may want to restrict the sample to pairs of composers in which both teacher and student were located in the same city and time. This approach, which

[11] As we have seen above, this is a limited concern in our context of music composition, since composers typically began lessons with their teachers at early ages and before they had composed anything themselves. It is also encouraging to observe that teacher-student pairs were not formed on the basis of quality considerations (see, e.g., fig. 2).

[12] In the appendix, we also explore and test other sources of contemporaneous direct influences (app. E1) and discuss in more detail why the influence of past masters does not affect our results (app. E2).

[13] A simple exploration of differences in mean similarity by connected status is shown in table B4.

TABLE 2
EFFECTS OF CONNECTION ON SIMILARITY (N = 23,489)

	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
Connected	.118**	.283***	.305***	.095**	.178***	.241***	.169***	.137***
	(.054)	(.092)	(.111)	(.039)	(.064)	(.091)	(.057)	(.045)
ln(Geographic distance)	−.015***	−.033***	−.040***	−.030***	−.022***	−.005	−.027***	−.011***
	(.004)	(.006)	(.008)	(.004)	(.006)	(.009)	(.004)	(.004)
ln(Time distance)	−.034***	−.046***	−.045***	−.031***	−.039***	−.039***	−.029***	−.036***
	(.006)	(.008)	(.010)	(.006)	(.008)	(.011)	(.009)	(.006)
R^2	.29	.32	.28	.37	.38	.33	.29	.21
Commonality controls	X	X	X	X	X	X	X	X
Composer fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

NOTE.—The point estimates presented are based on eq. (2). The dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key, and time signature (cols. 4–8, respectively) for a given pair of composers, i and j. "Connected" indicates realized teacher-student pairs, as identified in *Grove*. The reference group is conditioned to pairs in which the candidate teacher was alive for at least 1 year when the candidate student was between the ages of 5 and 30. Controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. Standard errors are clustered by candidate teacher. The data were collected by the authors (see sec. IV for details).

** $p < .05$.

*** $p < .01$.

effectively decreases the actual geographic distance between two composers to about zero, is pursued in appendix E3. To conduct this analysis, we extract from *Grove* the lifetime migration records for each composer, including the dates when a stay in a city began and ended. Table E3 shows the results for the regression that is conditional on city overlap during student's formation age and includes city fixed effects in addition to all previous controls. The effect of connection on similarity is positive and statistically significant, which provides important support for the findings.

The results are also robust to a number of alternative specifications, including truncating themes at six notes, measuring the similarity with the logged coefficient, or subsampling to European composers only or those born after the mid–eighteenth century, when originality became more valued. See appendix D2 for details.

B. Within-Conservatory Natural Experiments

The concern that students may self-select into a relationship with a particular teacher on the basis of his compositional style is limited. As we observed above, composers typically began lessons with their teachers at early ages—that is, when they were unlikely to have developed their own style of composing. Furthermore, it was very rare that students had actually composed before meeting the teacher.

Nonetheless, we pursue a natural experiment setting, exploiting teacher turnover at conservatories in order to identify more convincingly the effect a teacher may have had on his student. We estimate the student's similarity with his actual teacher at a given conservatory and compare it to the similarity with candidate teachers who had recently departed from or had not yet arrived at the given conservatory.[14] The pursued natural experimental design builds on the identification assumption that teacher turnover within a conservatory is uncorrelated with student characteristics. This assumption is plausible, insofar as students (or their parents) did not time enrollment at a conservatory according to whether a single teacher left or arrived at that institution. Considering the historical periods covered, the concern seems rather negligible, as travel and access to information were limited.

Table 3 reports the results in two panels for different time windows. For example, panel A shows the 10-year window, which narrows the risk set to candidate teachers who had departed from the conservatory during the preceding 10 years or would arrive at the conservatory in the following 10 years. The results show that a composer is, by about 0.2 standard

[14] Our data cover 94 composer pairs connected at a conservatory out of 1,064 pairs of composers who had a conservatory in common. The size of the risk set depends on the chosen time horizon for the analysis.

TABLE 3

WITHIN-CONSERVATORY NATURAL EXPERIMENTS

	PERCENT SHARED			COSINE SIMILARITY				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
				A. 10-Year Window				
Connected at conservatory	.083	.115	.265*	.117*	.163	.438***	.214**	−.021
	(.076)	(.122)	(.144)	(.062)	(.119)	(.169)	(.108)	(.071)
Observations	179	178	160	179	178	160	157	175
R^2	.11	.22	.18	.14	.26	.24	.23	.40
				B. 15-Year Window				
Connected at conservatory	.082	.103	.233*	.099*	.141	.400***	.194**	.016
	(.071)	(.118)	(.139)	(.057)	(.115)	(.161)	(.097)	(.070)
Observations	224	223	201	224	223	201	198	219
R^2	.10	.19	.15	.13	.23	.20	.20	.32
				Specifications				
Commonality controls	X	X	X	X	X	X	X	X
Conservatory fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

NOTE.—The dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key signature, and time signature (cols. 4–8, respectively) for a given pair of composers, *i* and *j*. “Connected at conservatory” indicates realized teacher-student pairs at a given conservatory. The reference group includes candidate teachers who recently departed from or did not yet arrive at the given conservatory. Controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. Standard errors are clustered by candidate teacher. The data were collected by the authors (see sec. IV for details).

* $p < .1$.

** $p < .05$.

*** $p < .01$.

deviations, more similar to his teacher at a conservatory (connected pair) than to candidate teachers who had recently departed from or were soon to arrive at the conservatory. There are no large differences between the observation windows.

These estimations are somewhat less precisely estimated than the baseline models, possibly a result of the lower number of connected composers. Nevertheless, the magnitude of the coefficients is comparable. Furthermore, as can be seen in table D6, the extent of a teacher's influence does not seem to depend on where teaching took place (conservatory vs. private education), which in turn extends the validity of the approach pursued here.

C. Composition-Level Similarity

Composers evolve over their life cycles and change style and mood in music as they age and absorb more knowledge; they also evolve internally. Therefore, identifying a single style of a composer is not an easy undertaking. The fact that we detect the influence of a teacher in the lifetime style (i.e., considering all compositions written) makes our result even stronger, since any eventual later-in-life deviations from the style imposed by the teacher would bias our coefficients downward. An emerging question is thus when the student is influenced the most and how long the influence lasts. To answer this, we examine data at the composition level and explore how similar a student is over time to his actual teacher, compared to candidate teachers. The analysis is conducted for teacher-student pairs for which we know the year they met as well as the year of composition of at least one work by the teacher and the student.[15]

We focus on the student's compositions after the meeting with a teacher because composers had typically not composed anything before meeting their teacher.[16] When it comes to the teacher, we consider only his output before the meeting. This is done in order to eliminate any concern of reverse causality, since a teacher may be also influenced by his student. Essentially, we estimate the similarity between the student's style at different times after the first meeting and the teacher's style before the meeting, and compare it to the similarity with styles of candidate teachers.

[15] An alternative approach to mitigate the concern of life-cycle variations in compositional styles is provided in app. E5. There we explore the teacher-student similarity across a range of variables that do not vary (much) over the lifetime (e.g., occupation or choice of musical instruments or musical forms). For example, it is highly improbable that a composer who is a pianist will become a violinist because of external influences (at least, not a violinist of a high enough quality to be mentioned in *Grove*).

[16] Appendix C2 describes the difficulty in obtaining information about the year of composition, which limits a composition-level analysis.

We also include a time-distance control to account for the number of years between the student's and the teacher's composition. This is done in order to account for changing fashions in style and to discount the importance of the teacher's compositions that had been written long before the meeting. We also introduce teacher-student pair fixed effects.

Table 4 shows the results. Interestingly, the teacher's influence is not constant over time. It is strong and statistically significant over a period of about 20 years after the meeting, after which the coefficients change signs. This implies that students eventually become more dissimilar to their actual teacher than to candidate teachers. The results may suggest that the style of a composer evolves over his lifetime and that a teacher's influence—while being significant initially—is not permanent. In other words, given enough time, a composer develops a style that allows him to differentiate from his teacher. Based on his own observations and discussions, Pfitzinger (2017) arrives at a similar conclusion, remarking that "some composers [are] using their teachers as a stepping stone rather than putting them on a pedestal." However, these results have to be interpreted with some caution, since the number of observations drops 20 and more years after a meeting.

D. *Multigenerational Similarity*

To further investigate the nature of the influence that a teacher has on students, we explore multigenerational persistence. The approach may provide additional insights into the longevity of a teacher's influence when students go on to become composition teachers themselves. We observed above that a student's style may change over time and could eventually even diverge from teacher's style. This raises the question of how durable a teacher's style is likely to be over multiple generations of students. In other words, does a student bear an imprint of his teacher's teachers?[17]

Extending our data beyond the 211 first-degree connections, we arrive at 193 second-degree, 104 third-degree, and 44 fourth-degree connections. We then reestimate our baseline model and present the results in table 5. The teacher's influence is visible and significant in the first generation, as argued above. We also observe that the influence persists through the next generation in a composer's musical lineage before it starts to fade. The coefficients remain positive into the third generation but are

[17] In sec. II, we describe the relevance of this approach to the literature on cultural transmission. However, the concern of multigenerational influence is also on the mind of many composers, including Pfitzinger, whose research originates from the following personal question (Pfitzinger 2017, xi): "If I am a compositional descendant of Beethoven or Mahler or Widor or Chadwick, has their compositional style affected me?"

TABLE 4
Effects of Connection on Similarity over Time, Estimated at the Composition Level

	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
After meeting:								
≤10 years	.374***	.268***	.110	.503***	.264***	.093	.050	−.134
	(.069)	(.072)	(.071)	(.091)	(.077)	(.064)	(.127)	(.120)
11–20 years	.624***	.391***	.155**	.603***	.323***	.168**	.379**	.344
	(.095)	(.096)	(.072)	(.116)	(.098)	(.073)	(.170)	(.233)
21–30 years	−.188	−.003	−.097	−.573***	−.381*	−.296	−.316	.344
	(.174)	(.179)	(.170)	(.203)	(.200)	(.184)	(.208)	(.233)
>30 years	−1.053***	−.859***	−.400*	−.662**	−.437*	−.328	−.256	.400
	(.227)	(.232)	(.230)	(.261)	(.254)	(.232)	(.325)	(.327)
Observations	958	958	958	958	958	958	741	944
R^2	.15	.05	.02	.10	.04	.03	.02	.06
Controls	X	X	X	X	X	X	X	X
Teacher-student pair fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

Note.—The dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key signature, and time signature (cols. 4–8, respectively) between the teacher's compositions before meeting the student and the student's compositions after the meeting. "After meeting" indicates four different time intervals at which composition-level similarity is measured: 0–10, 11–20, 21–30, and more than 30 years after the teacher-student meeting. The reference category is composition-level similarity between a given student and a candidate teacher. Controls not shown include time difference between the years when the two compared works were composed. Standard errors are clustered by candidate teacher. The data were collected by the authors (see sec. IV for details).

* $p < .1$.

** $p < .05$.

*** $p < .01$.

TABLE 5

Multigenerational Transmission (N = 45,736)

	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
Connected (first degree)	.109**	.275***	.299***	.104***	.179***	.239***	.191***	.174***
	(.054)	(.091)	(.112)	(.039)	(.062)	(.090)	(.058)	(.048)
Connected (second degree)	.096*	.175***	.160*	.158***	.202***	.258***	.082	.138**
	(.052)	(.067)	(.082)	(.059)	(.071)	(.098)	(.083)	(.059)
Connected (third degree)	.147	.047	−.084	.154**	.075	−.024	.005	.131
	(.144)	(.181)	(.197)	(.072)	(.118)	(.133)	(.126)	(.116)
Connected (fourth degree)	−.023	−.035	.011	−.015	.029	.149	−.047	.063
	(.079)	(.049)	(.044)	(.122)	(.133)	(.131)	(.110)	(.064)
R^2	.28	.30	.25	.33	.34	.31	.24	.22
Commonality controls	X	X	X	X	X	X	X	X
Distance controls	X	X	X	X	X	X	X	X
Composer fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

Note.—The dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key signature, and time signature (cols. 4–8, respectively) for a given pair of composers, i and j. "Connected" indicates realized teacher-student connections of the first degree (teacher-student), second degree (teacher-student's student), and so on. The reference group is conditioned for each generation to pairs in which the candidate teacher was alive for at least 1 year when the candidate student was between the ages of 5 and 30. Commonality controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. Distance controls not shown include logged geographic distance (in kilometers) and logged temporal distance (in years) between the birthplaces of two composers. Standard errors are clustered by candidate teacher. The data were collected by the authors (see sec. IV for details).

* $p < .1$.

** $p < .05$.

*** $p < .01$.

estimated with less precision. This is an interesting finding that points at the potentially multigenerational influence of a teacher.

E. *Horizontal Similarity*

The focus so far has been on direct teacher-student similarity. We now extend the analysis to explore the existence of any indirect effects by looking at similarities across pairs of students who had a teacher in common. Given the individualistic nature of composition teaching, students would not often have interacted. Furthermore, since the studies of two students with the same teacher did not usually overlap, most students would not even have met.

Despite the implicit restrictions of this test, it is encouraging to observe in table 6 that the similarity is significantly higher among students of the same teacher. The point estimates imply that students who had the same teacher are more similar to each other by about 0.1 standard deviations than they would be had they not had a teacher in common. This coefficient is about half the size of the effect observed directly between teachers and students, which supports the view that the teacher's influence is predominant.

VII. The Extent of Influence

The observation that teachers influence the compositional style of their students raises questions of the conditions under which this effect emerges and becomes prevalent. In this section, we restrict our sample to realized pairs only and exploit the heterogeneity of the observed influence by looking at factors that potentially matter for the extent of influence. In a methodological sense, this is equivalent to an exploration of the intensive margin. We build on our theoretical setup and quantify the extent of teacher influence as a function of his quality and investment of time in the student (panel A of table 7) and the student's subsequent career; that is, time to compose as well as exposure to other influences (panel B of table 7).

The first four specifications presented in table 7 disclose that the quality of the teacher is positively related to the extent of his influence: higher-quality teachers are more influential. For example, teachers with a 1% higher Murray quality index are up to almost a half–standard deviation more influential. Positive associations are also observed for the other three teacher-quality measures and are estimated with high precision across most specifications.

Next, we explore how the influence differs depending on the teacher's investment of time in the student, which is measured in two ways. First, we count the number of other students that the teacher had and observe a negative, albeit rarely statistically significant, relationship with similarity.

TABLE 6

Horizontal Similarity (N = 24,887)

	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
Connected (horizontal)	.110**	.152**	.111	.099**	.121*	.045	.011	.094**
	(.048)	(.072)	(.078)	(.039)	(.063)	(.079)	(.052)	(.040)
R^2	.01	.01	.01	.02	.02	.01	.01	.01
Commonality controls	X	X	X	X	X	X	X	X
Distance controls	X	X	X	X	X	X	X	X
Composer fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

Note.—The dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key signature, and time signature (cols. 4–8, respectively) for a given pair of composers, *i* and *j*. Explanatory variables are defined as follows. "Connected (horizontal)" indicates pairs of students who had a teacher in common. The reference group is conditioned to pairs in which the candidate teacher was alive for at least 1 year when the candidate student was between the ages of 5 and 30. Commonality controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. Distance controls not shown include logged geographic distance (in kilometers) and logged temporal distance (in years) between the birthplaces of two composers. Standard errors are clustered by candidate teacher. The data were collected by the authors (see sec. IV for details).

* $p < .1$.

** $p < .05$.

TABLE 7
EXTENT OF INFLUENCE

	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
	A. Teacher's Quality and Investment of Time in the Student ($N = 211$)							
ln(Teacher's Murray index)	.108	.360***	.467***	.170***	.358***	.388***	.206***	.159***
	(.066)	(.100)	(.127)	(.044)	(.075)	(.108)	(.055)	(.041)
R^2	.04	.11	.12	.13	.18	.15	.12	.09
ln(Teacher's Spotify followers)	.022	.153***	.213***	.079***	.191***	.242***	.080**	.020
	(.033)	(.050)	(.058)	(.022)	(.039)	(.052)	(.032)	(.024)
R^2	.02	.08	.10	.11	.19	.18	.09	.03
Spotify popularity score	.005	.025***	.032***	.012***	.029***	.035***	.011***	.004
	(.004)	(.007)	(.008)	(.003)	(.005)	(.006)	(.004)	(.003)
R^2	.03	.10	.12	.13	.22	.20	.09	.03
ln(Teacher's biography word count)	.110	.397***	.538***	.182***	.433***	.522***	.222***	.144***
	(.068)	(.106)	(.136)	(.042)	(.076)	(.110)	(.062)	(.047)
R^2	.03	.11	.14	.13	.22	.19	.12	.07
ln(Teacher's no. of students)	−.034	−.049	−.072	−.007	−.058	−.184**	.004	−.057
	(.053)	(.077)	(.081)	(.040)	(.068)	(.092)	(.050)	(.036)
R^2	.02	.03	.03	.05	.07	.09	.05	.03
ln(Teacher's writings word count)	.017	.085**	.095**	.025	.061*	.042	.050**	.027
	(.027)	(.043)	(.048)	(.018)	(.033)	(.043)	(.024)	(.018)
R^2	.02	.05	.05	.06	.09	.08	.07	.04

	B. Student's Time to Compose and Exposure to Other Influences							
Student composer has no other occupation	−.016	−.088	−.173	−.045	−.145	−.289	−.073	−.048
	(.130)	(.210)	(.265)	(.090)	(.163)	(.229)	(.128)	(.095)
Observations	211	211	211	211	211	211	211	211
R^2	.02	.03	.03	.05	.07	.08	.05	.03
Student's time to compose	−.010**	−.007	−.003	−.007**	−.007	−.007	−.010**	−.010**
	(.005)	(.007)	(.008)	(.003)	(.006)	(.008)	(.005)	(.004)
Observations	95	95	95	95	95	95	95	95
R^2	.10	.08	.06	.15	.12	.13	.09	.10
Student's no. of cities visited	−.026**	−.018	.002	−.013	−.021	.003	−.016	−.019
	(.012)	(.022)	(.027)	(.010)	(.018)	(.024)	(.012)	(.013)
Observations	211	211	211	211	211	211	211	211
R^2	.03	.03	.03	.06	.07	.07	.06	.04
	Specifications							
Commonality controls	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

Note.—The dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key signature, and time signature (cols. 4–8, respectively) for a realized teacher-student pair. Each panel reports a separate set of regressions using explanatory variables, defined as follows. Ln(Teacher's Murray index), ln(Teacher's Spotify followers), "Teacher's Spotify popularity," and ln(Teacher's biography word count) are the teacher's logged Murray quality index, logged number of Spotify followers, Spotify popularity score (0–100), and logged biography word count, respectively. Ln(Teacher's no. of students) is the logged number of a composer's students; ln(Teacher's writings word count) are the teacher's logged word count in the writings section of his biography. "Student composer has no other occupation" indicates students whose only listed occupation is that of a composer. "Student's time to compose" measures the number of years between the student's year of death and the year when he met with the teacher. "Student's no. of cities visited" is the number of cities that the student visited during his career. Controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. Standard errors are clustered by candidate teacher. The data were collected by the authors (see sec. IV for details).

* $p < .1$.
** $p < .05$.
*** $p < .01$.

This may suggest that composers who teach a higher number of students have less time to dedicate themselves to a single student and hence that their influence is potentially lower. Second, we approximate the teacher's effort invested in educating with the word count in the writings section of his biography. The writings section lists works that a composer has written and often includes pedagogical writings. The result suggests that the extent of influence increases as the teacher dedicates more time to pedagogical efforts.

In panel B of table 7, we analyze how the student's time to compose and exposure to other influences matter for the similarity with his teacher. First, we show results for students who have no occupation listed in *Grove* other than "composer." Those who do not also work as, for example, conductors or performers may have more time available to compose and, hence, better opportunities to develop their own styles. The point estimates are negative but remain statistically insignificant. Second, for the subsample of students for whom we know the year they met the teacher, we calculate the remaining years of life. Once again, having more time to compose may create opportunities to redevelop one's style. The regressions deliver consistently negative coefficients, which are often statistically significant. The last estimation explores the existence of a systematic difference in similarity to one's teacher, depending on the number of cities visited by the student throughout his career. It is conceivable that with more travel and increased exposure to other influences, the teacher's imprint fades away. However, as can be observed, the departure from the teacher's influence is very limited.

All in all, this section has shown that the influence of teachers is also observable at the intensive margin. Interestingly, it is predominantly the teacher's background (his quality) and actions (the investment of time and effort) that matter for the breadth of influence. On the other hand, the student, once exposed to the teacher's influence, appears to have limited possibilities to depart from it in ways other than through the passage of time.

VIII. Implications for Student Quality

A number of different approaches have consistently disclosed that teachers have an influence on the style of their students. A question that emerges is whether the observed influence causes only good ideas to persist or bad ones too. Or, more generally, What are the implications for the quality of a student depending on how much and whom he is imitating?

We explore these questions by investigating the interaction terms between teacher quality and the extent of imitation by the student. More precisely, we estimate what the probability is that the student is placed within the top-quality quartile as a function of teacher quality and the extent of teacher-student similarity. This approach enables us to shed some light on the returns from imitation depending on teacher quality.[18]

The results are shown in table 8, using Spotify followers as the quality measure (see tables B5, B6, and B7 for comparable results using other quality measures). Students are more likely to be placed in the top-quality quartile if they imitate higher-quality teachers. The estimated effect implies that being 1 standard deviation more similar to a top-quartile-quality teacher increases the probability of the student being placed in the top quartile by about 15%–20%. The positive effect remains significant and positive for composers influenced by teachers placed in the second quartile, albeit the point estimates tend to be smaller in size. Interestingly, the sign of the estimates changes for the bottom quartile: the negative coefficients imply that imitating low-quality teachers decreases the chance of the student being top quality himself.

These results suggest that imitation can be conducive to success, provided that the right role model is chosen, but otherwise it may become detrimental to one's chances of becoming successful.

IX. Role of Competition among Composers

A potentially important determinant of creativity is competition among composers. In particular, a high concentration of composers might lead to a competitive working environment, where only extraordinary performance is acknowledged (Borowiecki 2013). Competition could thus matter for the nature of borrowing and the novelty of compositions and hence have an effect on how a teacher influences a student.

In order to explore this possibility, we need to construct measures of competition among composers. The degree of competition is approximated with the number of other composers located in a given city and time. This approximation of competition should be fairly accurate, given the constrained supply of cultural infrastructure, the limited number of employers, and the winner-takes-all type of economy of music composition.[19]

[18] Self-selection into teacher-student connections based on quality would be a concern in most contexts. However, this is not necessarily the case for our sample, where we have observed that teacher-student matching does not appear to be based on quality considerations (see, e.g., fig. 2).

[19] In the earlier years, the pool of potential employers of a composer was fairly limited and comparable across cities (or countries), which had typically one ruler and one church. In later periods, most cities typically had at most one concert hall with one symphonic orchestra, at most one opera house with one opera company, and at most one conservatory (see sec. III and Borowiecki 2013, 2015b). In fact, from the nineteenth century onward, most larger cities have had exactly one concert hall and usually one opera house, a characteristic that is fairly independent of city size or wealth. It can be therefore expected that competition for these limited resources was potentially high, since the composer needed to outcompete rivals in order to test and perform his works. Therefore, the degree of competition was much related to the number of other composers located in the same city at the same time.

TABLE 8

STUDENT'S QUALITY AND IMITATION (N = 183)

	Student Is in Top Quartile of BM Composer Quality (Spotify Followers)							
	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
Teacher in >75th percentile × Std Sim	.200***	.154***	.110***	.271***	.178***	.123***	.210***	.172**
	(.044)	(.023)	(.021)	(.075)	(.039)	(.026)	(.057)	(.080)
Teacher in 50th–75th percentile × Std Sim	.157***	.101***	.096***	.172***	.083*	.049	.173**	.208***
	(.054)	(.034)	(.031)	(.066)	(.046)	(.036)	(.073)	(.070)
Teacher in 25th–50th percentile × Std Sim	.032	.049	.047	.230*	.107	.013	.155	.167*
	(.105)	(.063)	(.073)	(.131)	(.091)	(.071)	(.100)	(.088)
Teacher in <25th percentile × Std Sim	−.240**	−.157**	−.177**	.038	−.116	−.136	−.060	−.052
	(.111)	(.064)	(.074)	(.130)	(.081)	(.090)	(.074)	(.072)
R^2	.20	.23	.21	.17	.17	.16	.18	.14
Commonality controls	X	X	X	X	X	X	X	X
Teacher quality controls	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

NOTE.—The dependent variable indicates whether the student is in the top quartile of BM composer quality, measured by Spotify followers. Each column reports a separate set of regressions using similarity measures defined as follows. A standardized similarity coefficient ("Std Sim") that measures the percentage of collective 2-/3-/4-grams shared is shown in cols. 1–3. The cosine similarity of 2-/3-/4-grams, key signature, and time signature is shown in cols. 4–8. Commonality controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. Teacher quality controls not shown include dummies for teacher being in a given quality quartile. Standard errors are clustered by candidate teacher. The data were collected by the authors (see sec. IV for details).

* $p < .1$.

** $p < .05$.

*** $p < .01$.

To calculate competition measures, we use additional information on the lifetime migration histories of composers covered in our research. In particular, we count the number of composers located in each city and time.[20] The newly constructed measures are then used to explore the effect of competition on our similarity measures.

Table 9 shows results at the composer-city level, where the baseline model is extended by the logged number of composers located in the same city throughout history (panel A) and the logged number of composers located in the same city at the same time (panel B). Measuring competition in the same city throughout history, as opposed to at the same time, is motivated by the fact that music clusters have remained remarkably stable throughout centuries (e.g., O'Hagan and Borowiecki 2010), and the all-time aggregate may possibly provide some insight on the long-term culture and preference for music of a given society. However, the preferred estimation is the one that narrows the approach to the same time.

The results are compelling. First of all, it can be observed throughout both specifications that a student is more similar to his actual teacher and that the point estimates are comparable in size and significance with the baseline. This is encouraging, especially considering that the sample here is smaller because of the conditioning to city overlap of each realized or unrealized pair of composers and since the dates for city visits are known only for a subsample.

Second, the competition measures (number of other composers located in the same city) in panels A and B seem to suggest that with higher competition there is in general a lower similarity across composers. To put it differently, composers have a more distinct style if they are based in cities with a higher number of other composers. The associations are not estimated with high precision, but the consistency in the negative sign on the coefficients is insightful.[21]

We explore in appendix E4 whether and how competition matters for the connection to formalize. Other factors that could affect the formation of connections and the nature of a teacher's influence are explored in appendix E6, with a focus on the composer's class, wealth, or type of

[20] See app. E3 for details on the composer-city–level data.

[21] A number of robustness tests were conducted and include estimations in which the competition measures are calculated differently (at level, instead of logged, or as ratios, e.g., as the number of students per teacher in a city), the number of composers in the same city is considered in time intervals longer or shorter than a decade around the actual stay in a given city by a given composer, extremes (e.g., cities with the highest concentration of composers) are dropped, alternative competition measures are used that take account of composers quality (e.g., the total number of Murray index points, instead of the absolute/relative numbers of composers), or underlying conditions are changed (e.g., no overlap in city).

TABLE 9
EFFECTS OF COMPETITION ON SIMILARITY

	PERCENT SHARED			COSINE SIMILARITY				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
	A. Competition in Same City throughout History ($N = 5{,}757$)							
Connected	.093	.275***	.357***	.105**	.151**	.189**	.142***	.136***
	(.110)	(.096)	(.091)	(.041)	(.067)	(.087)	(.053)	(.032)
No. of composers in same city (logged)	−.014*	−.002	−.012	−.008	−.008	−.017	−.012	−.003
	(.008)	(.012)	(.011)	(.007)	(.011)	(.012)	(.009)	(.007)
R^2	.34	.36	.33	.41	.41	.36	.32	.27
	B. Competition in Same City Contemporaneously ($N = 5{,}757$)							
Connected	.093	.274***	.357***	.104**	.151**	.190**	.142**	.136***
	(.110)	(.096)	(.091)	(.041)	(.067)	(.087)	(.054)	(.032)
No. of composers in same city at same time (logged)	−.021**	−.007	−.014	−.013*	−.014	−.021*	−.021**	−.006
	(.008)	(.012)	(.012)	(.007)	(.010)	(.013)	(.010)	(.007)
R^2	.34	.36	.33	.41	.41	.36	.32	.27
	Specifications							
Commonality controls	X	X	X	X	X	X	X	X
Distance controls	X	X	X	X	X	X	X	X
Composer fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

NOTE.—The dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key and time signatures (cols. 4–8, respectively) for a given pair of composers. “Connected” indicates realized teacher-student pairs. Competition measures include the logged number of composers located in the same city throughout history (panel A) and the logged number of composers located in the same city in the same decade (panel B). The reference group is conditioned to pairs in which the candidate teacher was alive for at least 1 year when the candidate student was between the ages of 5 and 30 and to composer pairs (whether realized or unrealized) that overlapped in a city. Controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. Standard errors are clustered by candidate teacher. The data were collected by the authors (see sec. IV for details).

* $p < .1$.

** $p < .05$.

*** $p < .01$.

employer. Appendix D4 presents implications of religion for teaching, connecting, and composing.

X. Conclusion

The economics literature convincingly documents how teachers influence the quantity or quality of their students' output. A more subtle question is whether a teacher influences the style of work of a student—a concern of particular significance if one considers that it is a venture into a human's creative process and that creativity and ideas are transmitted across human relationships. The importance of a better understanding of the person-to-person transmission of creative style is also supported by the need to improve our knowledge about creative processes and how to enhance them.

The flow of ideas is clearly the cornerstone of scientific or artistic innovations, and yet—since an idea is such an elusive concept—it is very difficult to study directly how ideas are transmitted across people. Therefore, empirical evidence supporting the conventional wisdom that teachers influence the style of creative work of their students is scarce. This paper presents the first systematic analysis of the teacher effect on creative output, by exploiting a novel database on music compositions, which provides a unique opportunity to capture and measure some key attributes of creative output. Baseline estimates compare differences in style between a connected pair (student and his actual teacher) and unconnected pairs (student and candidate teachers—i.e., contemporaneous composers who were alive during the student's formation age but were unconnected with him). Across a number of different approaches, it is consistently shown that a student's work is on average about 0.2–0.3 standard deviations more similar to works by his actual teacher than to those of candidate teachers. The results also show that while the influence may not be permanent—it diminishes later in a composer's life—it is sufficiently durable and significant to transmit into subsequent generations.

To shed light on the conditions under which the influence is enhanced, we have exploited a composer's detailed biographical data. This has provided insight into the factors stimulating the influence (e.g., the quality of the teacher) and also into details that appear largely irrelevant for increased influence (the student's subsequent career). The analysis also provides valuable information on the implications of increased imitation by a student for his career and overall quality. Imitating above-average-quality teachers can be conducive to the student's lifetime quality, while the opposite effect is observed for imitation of teachers in the bottom quality quartile.

Our analysis is constrained to a small, albeit prominent and influential, group of composers. However, although the context and background (music and history) of this study are distinctive, the mechanisms and explanations examined here are likely applicable to most settings where creative output is produced. For example, the phenomenon of direct and indirect influences is relevant for other areas of the arts, for science, and for the cultural and creative sectors more generally. However, it is not only the categorization of style or the ways in which style is transmitted across human relationships that is important, but also the very specific question of whether and how teachers, mentors, or leaders influence the style of work of others, be it the work of students or that of junior colleagues. For a composer, being influenced by a low-quality teacher may deteriorate his future prospects and push cultural production away from its potential. If creators in the inventive sectors were similarly influenced by low-quality teachers or bad ideas, this could ultimately resonate in lower economic growth.

Some artists and scientists commit their lives to having lasting influence and becoming memorable. In doing so, they often prioritize artistic output or academic publications that are visible to their peers, critics, and employers. However, it may often be via teaching that the greatest influence occurs, when the teacher lives on as a reverberation in the work of the student.

Appendix A

Appendix Figures

Fig. A1.—Example of a theme: "Für Elise," by Ludwig van Beethoven. Cropped screenshot from Barlow and Morgenstern (1975, 50). Theme: E-D#-E-D#-E-B-D-C-A; transposed: G-F#-G-F#-G-D. Key signature: A minor (see sec. C1 for identifying major vs. minor keys). Time signature: 3/8. Pft. = fortepiano. Year of composition: 1810 (IMSLP 2016–19).

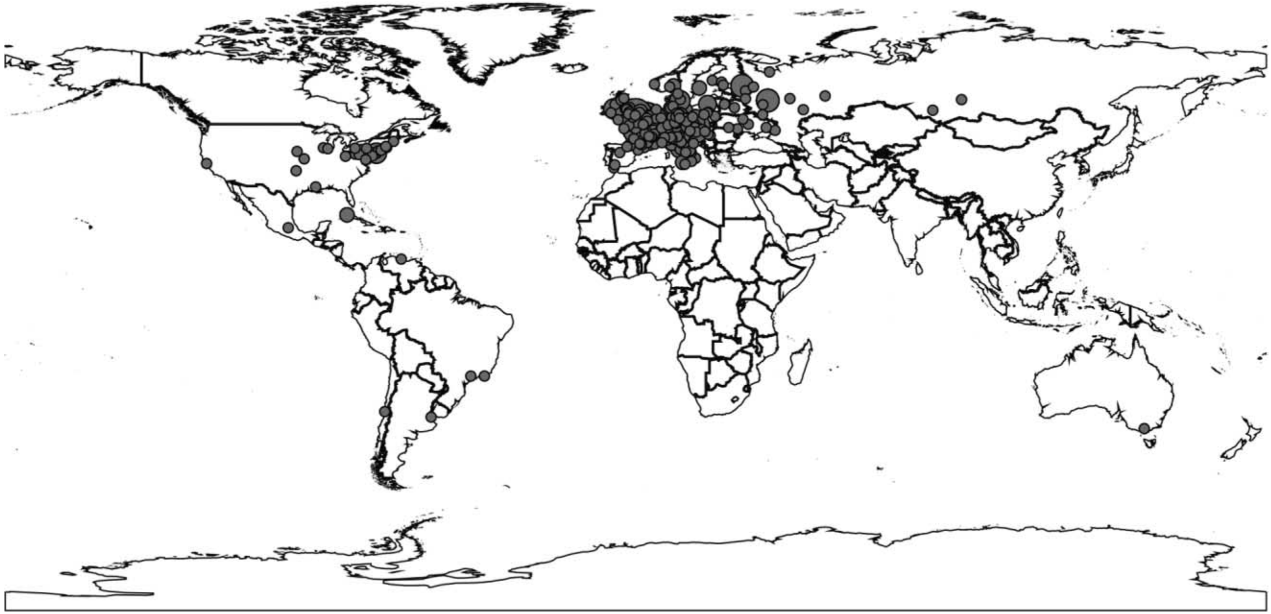

FIG. A2.—Birth location for composers listed in Barlow and Morgenstern (1975, 1976). The data were collected by the authors (see sec. IV for details). A color version of this figure is available online.

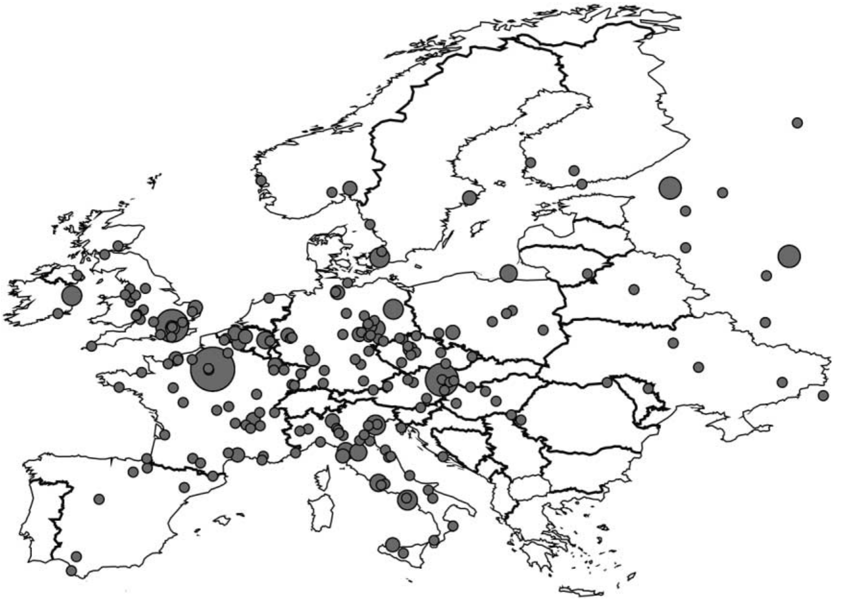

Fig. A3.—Birth location for composers born in Europe and listed in Barlow and Morgenstern (1975, 1976). The data were collected by the authors (see sec. IV for details). A color version of this figure is available online.

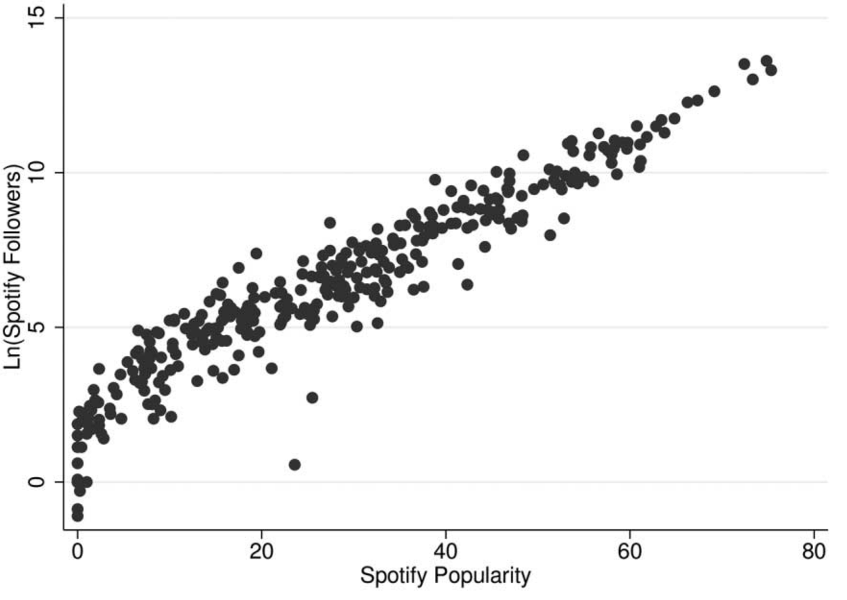

Fig. A4.—Spotify followers versus Spotify popularity: relationship between the logged number of Spotify followers (ln(Spotify Followers)) and Spotify popularity score (Spotify Popularity) measured on a scale from 0 to 100. The data are retrieved for each composer and month over a 12-month period from October 2016 to September 2017 and averaged out. See section IV for details. A color version of this figure is available online.

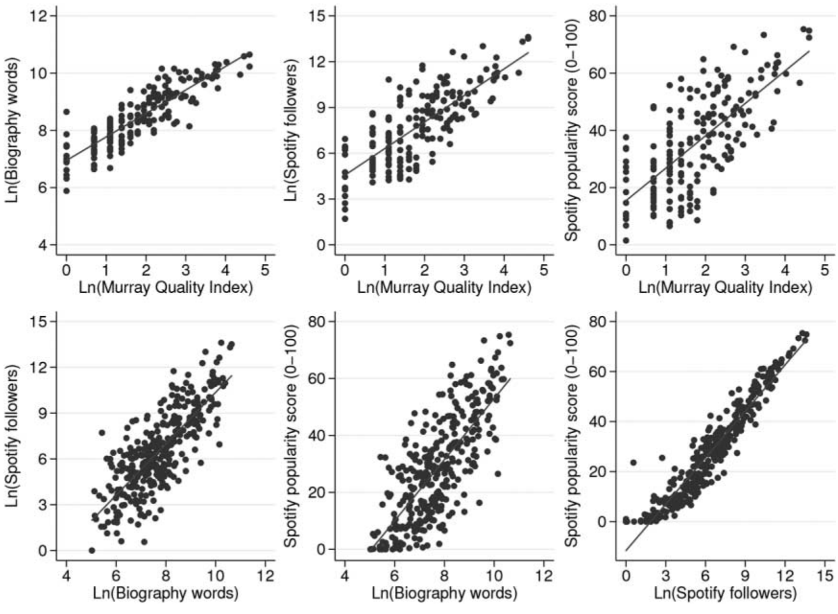

FIG. A5.—Scatterplots for composer quality: relationships between each of our four composer-quality measures: the logged Murray quality index (ln(Murray Quality Index)), the logged biography word count in the life section of an entry in *Grove* (ln(Biography words)), the logged number of Spotify followers (ln(Spotify followers)), and Spotify popularity score (0–100). The data were collected by the authors (see sec. IV for details). A color version of this figure is available online.

Appendix B

Appendix Tables

TABLE B1
SIMILARITY MEASURES FOR BARLOW AND MORGENSTERN (1975, 1976)
COMPOSER PAIRS (N = 28,546)

	Mean	SD	p10	p50	p90
Percent shared:					
1-grams	.71	.12	.54	.71	.88
2-grams	.37	.12	.22	.36	.54
3-grams	.13	.08	.05	.11	.24
4-grams	.04	.04	.00	.03	.09
Cosine similarity:					
1-grams	.89	.08	.79	.91	.97
2-grams	.61	.16	.38	.62	.82
3-grams	.30	.17	.09	.28	.55
4-grams	.12	.12	.00	.09	.29
Key signature	.35	.23	.00	.35	.67
Time signature	.55	.25	.19	.57	.86

NOTE.—Similarity coefficients measure the percentage of collective 1-/2-/3-/4-grams shared (rows 1–4, respectively) or the cosine similarity of 1-/2-/3-/4-grams, key, and time signature (rows 5–10, respectively) for a given pair of composers i and j; pn = nth percentile. The summary is restricted to pairs in which the older of the pair was alive when the younger was between ages 5 and 30. The data were collected by the authors (see sec. IV for details).

TABLE B2
DISTRIBUTION OF BM COMPOSERS BY CENTURY OF BIRTH

Century	Number	Percentage
Fourteenth	2	.6
Fifteenth	4	1.2
Sixteenth	19	5.6
Seventeenth	26	7.6
Eighteenth	44	12.9
Nineteenth	234	68.6
Twentieth	12	3.5
Total	341	100.0

NOTE.—Absolute and relative frequencies of composers listed in Barlow and Morgenstern (1975, 1976; BM) by century of birth. The data were collected by the authors (see sec. IV for details).

TABLE B3
COMPOSER LIFE SPANS AND AGE AT MEETING

	Mean	p5	p25	p50	p75	p95
Composer life span	67.37	39	57	70	79	89
Age at meeting teacher	18.19	6	14	18	22	30

NOTE.—Mean and percentiles (pn) of composers' life span (first row) and age at meeting teacher (second row). The data were collected by the authors (see sec. IV for details).

TABLE B4

Difference in Mean Similarity, by Connected Status

	Not Connected (1)	Connected (2)	Level Difference (3)	Difference (%) (4)
Percent shared:				
1-grams	.712	.739	.026***	4
2-grams	.369	.405	.037***	10
3-grams	.130	.161	.032***	24
4-grams	.040	.053	.013***	3
Cosine similarity:				
2-grams	.609	.674	.065***	11
3-grams	.304	.360	.056***	19
4-grams	.122	.153	.031***	25
Key signature	.353	.429	.076***	21
Time signature	.546	.632	.086***	16

Note.—Similarity coefficients measure the percentage of collective 1-/2-/3-/4-grams shared (rows 1–4, respectively) or the cosine similarity of 1-/2-/3-/4-grams, key, and time signature (rows 5–10, respectively) for a given pair of composers *i* and *j*. The sample is restricted to pairs in which the older of the pair was alive when the younger was between ages 5 and 30. Column 3 shows the *t*-test difference between teacher-student pairs (connected) and all other pairs (not connected). Column 4 indicates the magnitude of the difference.

*** $p < .01$.

TABLE B5

Student's Quality (Spotify Popularity) and Imitation ($N = 183$)

	Student Is in Top Quartile of BM Composer Quality (Spotify Popularity)							
	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
Teacher in >75th percentile × Std Sim	.219***	.175***	.155***	.356***	.218***	.147***	.326***	.293**
	(.055)	(.032)	(.031)	(.098)	(.056)	(.043)	(.102)	(.114)
Teacher in 50th–75th percentile × Std Sim	.220	.070	.034	.274	.193	.089	−.057	.396***
	(.272)	(.140)	(.119)	(.193)	(.136)	(.103)	(.161)	(.145)
Teacher in 25th–50th percentile × Std Sim	.157	.168**	.080	.317	.198	.057	.320***	.379*
	(.121)	(.084)	(.131)	(.204)	(.135)	(.070)	(.115)	(.199)
Teacher in <25th percentile × Std Sim	−.936*	−.030	.048	.926	.034	.199	−.046	−.125
	(.500)	(.548)	(.418)	(1.258)	(.396)	(.562)	(.313)	(.296)
R^2	.60	.62	.59	.59	.59	.56	.60	.60
Commonality controls	X	X	X	X	X	X	X	X
Teacher quality controls	X	X	X	X	X	X	X	X
Composer fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

Note.—The dependent variable is the probability of a student being in the top quartile of BM composer quality measured by the Spotify popularity score. See table 8 note for further details.

* $p < .1$.

** $p < .5$.

*** $p < .01$.

TABLE B6
STUDENT'S QUALITY (Murray Quality Index) AND IMITATION (N = 183)

	Student Is in Top Quartile of BM Composer Quality (Murray Quality Index)							
	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
Teacher in >75th percentile × Std Sim	.247***	.173***	.147***	.433***	.221***	.131***	.109	.149
	(.053)	(.032)	(.030)	(.103)	(.057)	(.043)	(.085)	(.109)
Teacher in 50th–75th percentile × Std Sim	.194	.167*	.134	.381**	.291***	.289***	.456***	.219
	(.132)	(.089)	(.096)	(.151)	(.097)	(.102)	(.111)	(.150)
Teacher in 25th–50th percentile × Std Sim	.065	.527	.071	.905**	.555*	.151	.155	.321*
	(.392)	(.509)	(.213)	(.354)	(.287)	(.165)	(.196)	(.189)
Teacher in <25th percentile × Std Sim	−.031	.012	−.208	−.001	.035	.021	.048	−.048
	(.042)	(.041)	(.204)	(.032)	(.036)	(.023)	(.069)	(.127)
R^2	.62	.64	.61	.63	.62	.59	.58	.55
Commonality controls	X	X	X	X	X	X	X	X
Teacher quality controls	X	X	X	X	X	X	X	X
Composer fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

NOTE.—The dependent variable indicates whether the student is in the top quartile of BM composer quality measured by Murray quality index. See table 8 note for further details.

* $p < .1$.
** $p < .5$.
*** $p < .01$.

TABLE B7

Student's Quality (Biography Words) and Imitation ($N = 183$)

	Student Is in Top Quartile of BM Composer Quality (Biography Words)							
	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
Teacher in >75th percentile × Std Sim	.147**	.109**	.098**	.257*	.169**	.140***	.085	.114
	(.072)	(.047)	(.043)	(.133)	(.072)	(.051)	(.083)	(.121)
Teacher in 50th–75th percentile × Std Sim	.171**	.115*	.108*	.105	.112	.097	.279***	.112
	(.081)	(.060)	(.060)	(.128)	(.085)	(.074)	(.099)	(.095)
Teacher in 25th–50th percentile × Std Sim	−.038	.175	.128	.625***	.326***	.196*	.220	.274
	(.149)	(.136)	(.150)	(.234)	(.105)	(.099)	(.156)	(.179)
Teacher in <25th percentile × Std Sim	.236	.209	.350*	.241	.125	.059	−.011	.272
	(.236)	(.206)	(.207)	(.220)	(.122)	(.070)	(.193)	(.192)
R^2	.57	.58	.58	.59	.60	.57	.58	.56
Commonality controls	X	X	X	X	X	X	X	X
Teacher quality controls	X	X	X	X	X	X	X	X
Composer fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

Note.—The dependent variable indicates whether the student is in the top quartile of BM composer quality measured by biography word count. See table 8 note for further details.

* $p < .1$.

** $p < .5$.

*** $p < .01$.

Appendix C

Further Details on Data

C1. Identifying Key Signature

Every key signature represents both a major key and a minor key (e.g., an empty key signature is either C major or A minor). To identify major versus minor keys, we perform several tests. First, we look for an early note in a theme matching the major or minor key (often, the first note is the tonic note of the key). Second, we count tonic notes of the major versus the minor key in the theme. Third, we count tonic chord notes of the major versus the minor key. We then validate the predictive power of these tests against a sample of about 850 themes for which the true major or minor key is known from title of the work (e.g., "Prelude in C# Minor"). Using combinations of tests with high predictive power enables us to estimate the true key signature with a relatively high precision (accuracy rates of >90%).

C2. Year of Composition

We use the International Music Score Library Project (IMSLP 2016–19) in order to collect the year of composition for each of the works covered by Barlow and Morgenstern (1975, 1976). The IMSLP is recognized by the scientific community as one of the most comprehensive resources on music scores. Nonetheless, we encounter several challenges. First, the IMSLP does not include all our composers and omits, in particular, individuals whose works are still under copyright. Second, it is often not possible to uniquely match a work from the BM dictionaries with the IMSLP. Third, for many works the year of composition is unknown or missing.[22]

All in all, we collect data on the composition years for 66.9% of our themes. For about two-thirds of these themes the composition year is a single year, whereas for the remaining ca. 4,000 themes it is provided in a relatively wide range (average: 5.49 years, standard deviation: 7.81), during which the work has been—or is thought to have been—written. In the baseline models, we consider the minimum of this range in order to capture when the creative process of composing began, but the results would not change qualitatively if instead we used the average. In addition, 5% of themes with known composition years are provided with uncertainty (e.g., indicated with the word "circa," a question mark, or similar). For these reasons, the analysis at the composition level has to be interpreted with some caution.

[22] In a pilot study, we collected years of first performance and first publication of a work, with the aim of predicting the year of composition. However, the years of first performance and publication are mostly missing, unknown, or unavailable. Furthermore, there exists a very significant variation between these years and the year of composition (e.g., not rarely have works been first performed or published many years after the composer died).

Appendix D

Further Tests

D1. Alternative Conditions

The choice of the control group is important, but as can be seen in this section, the results are not particularly sensitive to variations in the risk set. The overall aim of the conditions imposed is to narrow down the sample to pairs in which there was a reasonable probability for the formation of a teacher-student relationship. This is why our baseline condition restricts our analysis to pairs of composers in which the older of the two composers in a pair was alive for at least 1 year while the younger was in his "formation age," which we define as being between the ages of 5 and 30. This condition holds for all realized pairs (i.e., none of the actual pairs is dropped) and restricts all pairs to the same time period. In the remainder of this section, we discuss alterations to the conditioning by considering other time and geographic cutoff values.

D1.1. Conditioning to Same Time Period

We explore a number of other ways to condition to the same time period. The tests are reported in table D1 as follows: panel A shows the baseline, where we condition to pairs in which the candidate teacher was alive when the candidate student was aged 5–30; panel B shows the least restrictive estimation, where no conditions are imposed; in panel C, we condition to teachers and students whose lives overlapped by at least 1 year; in panel D, we condition to teachers and students whose lives overlapped by at least 10 years; in panel E, we condition to pairs in which the student was born during the teacher's lifetime; in panel F, we condition to pairs in which the teacher was alive when the student was between the ages of 10 and 25; in panel G, we condition to pairs in which the teacher was alive when student was between the ages of 15 and 20. Throughout these tests, the main change is observed in the size of the benchmark, which matters for the number of observations. It can be concluded that the results remain robust in each of these specifications.

TABLE D1

Effects of Connection on Similarity: Conditioning to Same Time Period

	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
	A. Baseline Condition: Teacher Was Alive When Student Was Aged 5–30 (N = 23,489)							
Connected	.118**	.283***	.305***	.095**	.178***	.241***	.169***	.137***
	(.054)	(.092)	(.111)	(.039)	(.064)	(.091)	(.057)	(.045)
R^2	.29	.32	.28	.37	.38	.33	.29	.21
	B. Alternative Condition: No Conditions (N = 45,736)							
Connected	.106**	.272***	.297***	.100**	.175***	.234**	.190***	.171***
	(.054)	(.091)	(.112)	(.039)	(.062)	(.090)	(.057)	(.048)
R^2	.28	.30	.25	.33	.34	.31	.24	.22
	C. Alternative Condition: Lives of Teacher and Student Overlapped (N = 24,542)							
Connected	.109**	.267***	.284**	.091**	.164**	.217**	.153***	.137***
	(.055)	(.092)	(.113)	(.039)	(.064)	(.090)	(.058)	(.044)
R^2	.29	.32	.28	.37	.37	.33	.29	.20
	D. Alternative Condition: Lives of Teacher and Student Overlapped by at Least 10 Years (N = 22,303)							
Connected	.115**	.279***	.298***	.090**	.172***	.234**	.171***	.129***
	(.054)	(.093)	(.111)	(.039)	(.064)	(.091)	(.057)	(.044)
R^2	.30	.32	.29	.38	.38	.33	.29	.21
	E. Alternative Condition: Student Born during Teacher's Lifetime (N = 24,542)							
Connected	.109**	.267***	.284**	.091**	.164**	.217**	.153***	.137***
	(.055)	(.092)	(.113)	(.039)	(.064)	(.090)	(.058)	(.044)
R^2	.29	.32	.28	.37	.37	.33	.29	.20

	F. Alternative Condition: Teacher Was Alive When Student Was Aged 10–25 (N = 22,303)							
Connected	.115**	.279***	.298***	.090**	.172***	.234**	.171***	.129***
	(.054)	(.093)	(.111)	(.039)	(.064)	(.091)	(.057)	(.044)
R^2	.30	.32	.29	.38	.38	.33	.29	.21
	G. Alternative Condition: Teacher Was Alive When Student Was Aged 15–20 (N = 20,970)							
Connected	.111**	.275***	.293**	.083**	.162**	.224**	.160***	.119***
	(.055)	(.093)	(.114)	(.039)	(.065)	(.092)	(.057)	(.043)
R^2	.30	.33	.29	.38	.38	.33	.29	.21
	Specifications							
Commonality controls	X	X	X	X	X	X	X	X
Distance controls	X	X	X	X	X	X	X	X
Composer fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

NOTE.—The dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key, and time signature (cols. 4–8, respectively) for a given pair of composers. “Connected” indicates realized teacher-student pairs. The reference group is conditioned as summarized in each panel title. Controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. Standard errors are clustered by candidate teacher.

** $p < .05$.

*** $p < .01$.

D1.2. Conditioning to Geographic Proximity

In addition to restricting in the baseline to pairs in which both composers lived in the same period, one may want to condition further to pairs of composers who lived in geographic proximity. We begin this analysis by additionally restricting the analysis to pairs in which both composers have the same country of birth (panel A of table D2), since being born in the same country may facilitate the formation of connections within the borders of the same country. Alternatively, one may argue that the cost of connecting is lower for composers of the same nationality, who share a similar culture, usually speak the same language, and so on. Therefore, panel B shows a regression that restricts to pairs in which both composers have the same nationality. The conducted tests are demanding. For example, restricting pairs to those who have the country of birth or nationality in common leads to an exclusion of about half of realized pairs. It is thus encouraging to observe that the results remain robust throughout the specifications.

TABLE D2

Effects of Connection on Similarity: Conditioning to Geographic or Cultural Proximity

	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
	A. Alternative Condition: Teacher and Student Born in Same Country (N = 2,192)							
Connected	.222***	.498***	.517***	.205***	.362***	.365**	.239**	.111
	(.079)	(.133)	(.168)	(.062)	(.105)	(.141)	(.095)	(.079)
R^2	.40	.42	.39	.46	.49	.47	.39	.33
	B. Alternative Condition: Teacher and Student Share Nationality (N = 2,627)							
Connected	.190**	.399***	.394**	.172***	.257**	.292**	.196**	.141*
	(.074)	(.143)	(.182)	(.059)	(.105)	(.135)	(.083)	(.076)
R^2	.38	.40	.37	.43	.45	.43	.36	.33
	Specifications							
Commonality controls	X	X	X	X	X	X	X	X
Distance controls	X	X	X	X	X	X	X	X
Composer fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

Note.—The dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key, and time signature (cols. 4–8, respectively) for a given pair of composers. “Connected” indicates realized teacher-student pairs. The reference group is conditioned to pairs in which the candidate teacher was alive for at least 1 year when the candidate student was between the ages of 5 and 30, and additionally it is conditioned as summarized in each panel title. Controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. Standard errors are clustered by candidate teacher.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

Finally, we pursue the most restrictive condition, in which we require composer pairs to be located in the same city and time. These estimations are presented in appendix E3 and once again reconfirm the baseline findings.

D2. Robustness Tests

D2.1. Alternative Specifications

The baseline results showing the effects of connection on similarity (see table 2) are robust to a number of alternative specifications. We summarize the robustness tests in table D3. Panel A repeats the baseline coefficients from table 2. Panel B presents the results for themes truncated at six notes. Panel C restricts the sample to pairs of composers born in Europe. Panel D shows the estimates for a subsample of composers born after 1750; we drop the early years, when originality was not valued very highly nor was there potentially much freedom for creativity.[23] Panel E restricts the sample to pairs of composers in which the actual or candidate teacher died after 1920. By doing this, we drop the most recent period, which is characterized by the onset of modern broadcasting technologies, such as radio and later television. Panel F shows models where each of the dependent variables has been logged instead of standardized.

[23] See sec. III for historical context on music originality. We also explore how the originality of a composer, measured as the inverse of similarity with past composers, matters for popularity and success. These explorations have turned so fertile that they have led to a spin-off project (see Borowiecki and Mauri 2021). However, it is instructive to note here that there does not appear to be any clear relationship between originality and the number of teachers or their quality.

TABLE D3
Robustness Tests: Different Specifications and Subsampling

	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
	A. Baseline (Table 2 N = 23,489)							
Connected	.118**	.283***	.305***	.095**	.178***	.241***	.169***	.137***
	(.054)	(.092)	(.111)	(.039)	(.064)	(.091)	(.057)	(.045)
R^2	.29	.32	.28	.37	.38	.33	.29	.21
Sample	World	World	World	World	World	World	World	World
	B. Themes Truncated at 6 Notes (N = 23,489)							
Connected	.099*	.195**	.150*	.102**	.149**	.156**	.169***	.137***
	(.056)	(.086)	(.079)	(.039)	(.058)	(.063)	(.057)	(.045)
R^2	.30	.29	.20	.39	.42	.44	.29	.21
Sample	World	World	World	World	World	World	World	World
	C. Only Composers Born in Europe (N = 17,370)							
Connected	.184***	.351***	.372***	.131***	.212***	.240**	.211***	.134***
	(.057)	(.098)	(.118)	(.044)	(.073)	(.099)	(.058)	(.047)
R^2	.28	.31	.29	.37	.38	.34	.30	.22
Sample	Europe	Europe	Europe	Europe	Europe	Europe	Europe	Europe

TABLE D3 (*Continued*)

	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
	D. Only Composers Born after 1750 (N = 22,947)							
Connected	.118**	.292***	.309***	.095**	.173***	.234**	.168***	.137***
	(.055)	(.094)	(.112)	(.039)	(.065)	(.092)	(.058)	(.046)
R^2	.29	.32	.28	.37	.38	.33	.29	.20
Sample	Drop pre-1750	Drop pre-1750	Drop pre-1750	Drop pre-1750	Drop pre-1750	Drop pre-1750	Drop pre-1750	Drop pre-1750
	E. Period of Commercial Broadcasting Dropped (N = 12,610)							
Connected	.139*	.357**	.374**	.141***	.246***	.263*	.154**	.174***
	(.078)	(.144)	(.176)	(.054)	(.091)	(.137)	(.064)	(.053)
R^2	.24	.29	.27	.35	.37	.33	.26	.22
Sample	Drop post-1920	Drop post-1920	Drop post-1920	Drop post-1920	Drop post-1920	Drop post-1920	Drop post-1920	Drop post-1920

	F. Logged Dependent Variable							
Connected	.040**	.115***	.145***	.036**	.094***	.151***	.118***	.100***
	(.019)	(.037)	(.054)	(.016)	(.036)	(.054)	(.041)	(.034)
Observations	23,489	23,288	20,305	23,489	23,288	20,305	20,223	23,012
R^2	.31	.31	.21	.35	.33	.27	.18	.18
Sample	World	World	World	World	World	World	World	World
	Specifications							
Commonality Controls	X	X	X	X	X	X	X	X
Distance Controls	X	X	X	X	X	X	X	X
Composer FE	X	X	X	X	X	X	X	X

NOTE.—The dependent variable is a standardized (panels A–E) or logged (panel F) similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key, and time signature (cols. 4–8, respectively) for a given pair of composers i and j. Standard errors are clustered by candidate teacher. See app. D3 for details.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

D2.2. Including Bins of Distance Terms

All baseline specifications include controls for the geographic distance (logged, in kilometers) and time distance (logged, in years). The logged variables take account of the potentially nonlinear relationship of large geographic or temporal distances. Alternatively, one may want to take more explicit account of potential nonlinearity by including bins of distance terms. We generate a set of geographic dummies to indicate pairs of composers who were born 100–250, 250–500, 500–1,000, or more than 1,000 km apart. We also generate a set of time dummies to indicate pairs of composers who were born 0–10, 10–25, 25–50, or 50–100 years apart. The results are shown in table D4. First, it can be observed that most of the geographic distance bins do not differ significantly from the baseline of pairs of composers born less than 100 km apart, albeit the point estimates are typically negative and increase with distance, so that pairs of composers born over 1,000 km apart are found to be more dissimilar. This may reflect a greater divergence in compositional style between composers born on different continents. Second, coefficients on each of the time bins are estimated with considerably greater precision and suggest the existence of larger decreases in similarity relative to the baseline (pairs born less than 10 years apart) and also across each of the bins (the point estimates increase significantly in absolute terms for each greater time interval). These results suggest that compositional style varies potentially more widely across generations of composers than across space. Third and most importantly, it is reassuring that throughout all these alterations and subsampling approaches the results on teacher influence remain very stable.

TABLE D4

Robustness Test: Effects of Connection on Similarity with Nonlinear Distance Controls (N = 23,489)

	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
Connected	.103*	.261***	.282**	.088**	.162**	.218**	.157***	.125***
	(.054)	(.093)	(.112)	(.040)	(.065)	(.092)	(.058)	(.045)
Geographic distance:								
100–250 km	.005	−.063	−.023	.003	.021	.070	.025	−.027
	(.046)	(.066)	(.074)	(.035)	(.056)	(.076)	(.043)	(.042)
250–500 km	−.045	−.065	−.013	−.027	.043	.109	−.004	−.028
	(.040)	(.062)	(.071)	(.032)	(.051)	(.068)	(.043)	(.039)
500–1,000 km	−.027	−.048	−.017	−.002	.044	.091	−.041	−.025
	(.044)	(.065)	(.075)	(.033)	(.056)	(.078)	(.043)	(.037)
>1,000 km	−.061	−.149**	−.124	−.072**	−.040	.030	−.095**	−.030
	(.044)	(.065)	(.076)	(.033)	(.055)	(.077)	(.044)	(.037)
Time distance:								
10–25 years	−.032***	−.041**	−.031	−.031***	−.040**	−.029	−.046***	−.042***
	(.012)	(.016)	(.019)	(.011)	(.017)	(.022)	(.017)	(.013)
25–50 years	−.110***	−.174***	−.166***	−.102***	−.157***	−.147***	−.161***	−.135***
	(.014)	(.025)	(.028)	(.013)	(.022)	(.026)	(.024)	(.015)
50–100 years	−.256***	−.388***	−.389***	−.208***	−.326***	−.342***	−.292***	−.283***
	(.021)	(.041)	(.047)	(.020)	(.032)	(.040)	(.033)	(.022)
R^2	.30	.32	.29	.37	.38	.33	.29	.21
Commonality controls	X	X	X	X	X	X	X	X
Composer fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

Note.—The dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key, and time signature (cols. 4–8, respectively) for a given pair of composers, i and j. "Connected" indicates realized teacher-student pairs. The reference group is conditioned to pairs in which the candidate teacher was alive for at least 1 year when the candidate student was between the ages of 5 and 30. Controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. The baseline are pairs of composers born less than 100 km apart and less than 10 years apart. Standard errors are clustered by candidate teacher. The data were collected by the authors (see sec. IV for details).

* $p < .1$.

** $p < .05$.

*** $p < .01$.

D3. Validity Tests

Here we pursue several attempts to provide further support to the validity of our methodology. First, we demonstrate that a composer's style relates to other works from the same location and period. Second, we show that our results resonate with theories propagated within musicology.

In the arts, style is a "distinctive manner which permits the grouping of works into related categories" (Fernie 1995, 361), and it is often divided into the general styles of countries or periods and also the interaction of the two. Using an unrestricted set of composer pairs, we regress each of our eight similarity measures on either an indicator for common birth country, common birth country interacted with common time period, common birth city, or geographic or temporal distance between birthplaces. Table D5 presents the results. As one would expect, a common location and/or time period implies a more similar style for the pair in question, whereas the opposite is true for greater geographic or temporal distance between birthplaces of two composers. Bringing these results into perspective: to be born in the same country increases similarity by about one-fourth of a teacher's influence on style similarity. The location and period are thus significant factors in determining a person's style, albeit they are markedly less dominant than a teacher's influence.

TABLE D5
Validity Tests: Similarity across Works from Same Time and Place

	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
	A. Common Birth Country (N = 57,970)							
Common birth country	.0526***	.113***	.150***	.0522***	.0832***	.0991***	.0142	.0802***
	(.0109)	(.0152)	(.0168)	(.00855)	(.0132)	(.0169)	(.0121)	(.0103)
R^2	.262	.281	.241	.356	.351	.299	.215	.208
	B. Common Birth Country and 50-Year Period (N = 57,970)							
Common birth country × period (50-year)	.0433***	.0945***	.121***	.0603***	.0830***	.0985***	.0726***	.175***
	(.0151)	(.0212)	(.0235)	(.0119)	(.0184)	(.0235)	(.0168)	(.0144)
R^2	.261	.281	.240	.356	.351	.299	.215	.210
	C. Common Birth City (N = 57,970)							
Common birth city	.0833**	.123**	.0994*	.0194	−.0194	−.0639	.0109	.253***
	(.0382)	(.0534)	(.0592)	(.0301)	(.0463)	(.0594)	(.0424)	(.0363)
R^2	.261	.281	.240	.356	.351	.299	.215	.208

TABLE D5 (*Continued*)

	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
	D. Geographic Distance Apart (N = 57,970)							
ln(Geographic distance)	−.0370***	−.0736***	−.0903***	−.0420***	−.0684***	−.0810***	−.0318***	−.0343***
	(.00284)	(.00397)	(.00439)	(.00223)	(.00343)	(.00441)	(.00315)	(.00270)
R^2	.264	.285	.245	.360	.355	.303	.216	.210
	E. Temporal Distance Apart (N = 57,970)							
ln(Time distance)	−.00861***	−.0219***	−.0256***	−.0173***	−.0235***	−.0315***	−.0367***	−.0653***
	(.00251)	(.00351)	(.00389)	(.00198)	(.00304)	(.00390)	(.00279)	(.00237)
R^2	.261	.281	.240	.357	.351	.300	.217	.218
	Specifications							
Composer fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

Note.—The dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key, and time signature (cols. 4–8, respectively) for a given pair of composers i and j. Standard errors are clustered by candidate teacher. The data were collected by the authors (see sec. IV for details).

* $p < .1$.

** $p < .05$.

*** $p < .01$.

Next, we explore whether there exists a systematic difference in the influence depending on whether the education takes place in the formal, institutional setting of a conservatory or has an informal character (e.g., private tuition). The expectation in musicology is the absence of any difference: "Whether the [teacher-student] relationship involves years of personal mentoring or simply attending a master class, the respect we have for these composers urges us to make their teachings part of ourselves, part of who we are as composers" (Pfitzinger 2017, xi). The regressions are shown in table D6 and deliver insignificant estimates, which do not support the notion that influence depends on the educational setting or type of teaching relationship. This result is encouraging, as it is in line with musicologists' understanding of a composer's teaching influence.

TABLE D6
VALIDITY TEST: NO DIFFERENCE BETWEEN FORMAL AND INFORMAL SETTING OF EDUCATION ($N = 154$)

	PERCENT SHARED			COSINE SIMILARITY				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
Conservatory education	.016	−.077	−.230	.009	−.066	−.208	.048	−.113
	(.168)	(.278)	(.351)	(.112)	(.201)	(.285)	(.144)	(.113)
R^2	.04	.07	.06	.10	.13	.11	.13	.06
Commonality controls	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

NOTE.—The dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key, and time signature (cols. 4–8, respectively) for realized teacher-student pairs. "Conservatory education" indicates realized pairs whose teaching took place at a conservatory. Controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. Standard errors are clustered by candidate teacher. The data were collected by the authors (see sec. IV for details).

Finally, we study the differences in similarity of realized teacher-student pairs across musical periods and show that the only detectable difference in similarity over time relative to the Renaissance is observable for the key signature. Since the key signature saw the largest developments in the sixteenth and seventeenth centuries, this is another finding that resonates with music history scholarship (see app. E7).

D4. Implications of Religion for Teaching, Connecting, and Composing

The historical context has implicitly shown that throughout history the institution of the church has played a role in music education and composition. This is neither a surprising fact nor is it specific to music, but it may give rise to questions of whether the religious denomination of a composer matters for the teaching or composing. We approach this in three parts, by looking at how the composer's religious background matters for his involvement in teaching, for the probability of two composers connecting, and for composition outcomes. But first, we need the data.

Initially, we collected data on the religious background of composers from biographical entries in *Grove*. However, the religious denomination was provided for only 27 composers. This is an interesting finding in itself. Building on the assumption that *Grove* provides only the most relevant information for a composer, the very limited records on religious background may suggest that it is rarely regarded as a determining factor in a composer's career.

We then used additional sources. We began searching for publications listed in JSTOR that cover composers and their religious background; then we proceeded to other online and offline biographies of composers; and in last instance, we searched additional online resources (e.g., articles in classical music magazines). These efforts enabled us to obtain the religious background for 151 composers. The main denominations are Catholic (38%,) Jewish (22%), and Protestant (20%). There are also 12% of composers who have no religion (five atheists, two agnostics, and 10 described as nonreligious).[24]

We begin with an exploration of how a composer's background matters for his involvement in teaching or studying and summarize the findings in columns 1–5 of panel A in table D7. Here we consider one of the following five dependent variables: a dummy variable for whether the composer has an occupation listed in *Grove* as a teacher (col. 1; see app. E5 for more details), a dummy for whether the composer taught another BM composer (col. 2), the number of BM students (col. 3), a dummy for whether the composer studied with another BM composer (col. 4), and a given composer's number of BM teachers (col. 5). Among the three main religions, the only significant coefficient is found for Protestants, who are about 21% more likely than nonreligious composers to have a teacher occupation listed in *Grove*. This may be due to the Protestant emphasis laid on education, but it has to be observed that the difference relative to Catholic or Jewish composers is much smaller and insignificant.

Second, we analyze whether there are any differences in the probability of forming a teacher-student connection based on having a religion in common. It can be seen in column 6 of panel A in table D7 that the estimate on the common-religion indicator is very small and statistically insignificant. This suggests that the religious background of the teacher and student did not determine the probability of connecting, but instead that matching may have been taking place across religious boundaries.

Indeed, we observe different religious beliefs for 30 out of 70 realized teacher-student pairs in which we know the religious background of both composers. In particular, teacher-student connections have been formed between Catholics and Jews (seven realized pairs), Catholics and Protestants (four), and Protestants and Jews (two), but mostly when one of the composers is nonreligious (13).

[24] Three side remarks are in order. First, comparing the full data on religious background (151 observations) with the small sample from *Grove* (27 observations), we observe very similar shares across the different denominations. This indicates that there is unlikely to be a bias in *Grove* with regard to religion. Second, all estimations that follow would also hold for the 27 observations from *Grove*, but their volatility would naturally increase. Third, Felix Mendelssohn is an interesting individual who converted from Judaism to Protestantism at the age of 7; we record him as a Protestant, which is the religious denomination of his time as a composer.

The absence of any clear pattern when it comes to the formation of educational connections is encouraging. Nonetheless, to reconfirm our baseline results on stylistic similarity between student and teacher, we add a robustness test of the control for common religion. The results are shown in panel B of table D7. Alternatively, one may want to estimate the baseline with additional variables that indicate whether either the candidate/realized teacher or the candidate/realized student had a particular religious denomination. This is shown in panel C of table D7. Both estimations support the robustness of the teacher's influence.

TABLE D7

Effects of Religion on Teaching, Connecting, and Composing

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Effects of Religion on Educational Involvement and Connection							
	Teacher Occupation	Realized Teacher	No. of Students	Realized Students	No. of Teachers	Connected		
Catholic	.137	.00734	.281	−.0284	−.0576			
	(.105)	(.130)	(.578)	(.135)	(.248)			
Protestant	.210*	−.0153	.161	.0527	.0994			
	(.116)	(.145)	(.642)	(.150)	(.275)			
Jewish	.136	−.193	−.443	.0143	−.0372			
	(.107)	(.133)	(.588)	(.137)	(.252)			
Other	.258*	−.160	1.459*	.499**	.678*			
	(.154)	(.192)	(.852)	(.199)	(.366)			
Common religion						.00536		
						(.00353)		
Observations	151	151	151	151	151	4,015		
R^2	.028	.057	.057	.036	.059	.097		
Century fixed effects	X	X	X	X	X			
Continent fixed effects	X	X	X	X	X			
Commonality controls						X		
Distance controls						X		
Composer fixed effects						X		
Sample	World	World	World	World	World	World		
	Percent Shared			Cosine Similarity				
	2-Grams	3-Grams	4-Grams	2-Grams	3-Grams	4-Grams	Key	Time
	B. Effects of Connection on Similarity: Adding a Control for Common Religion (N = 4,015)							
Connected	.243**	.493**	.544**	.179***	.265**	.261	.307***	.140
	(.120)	(.215)	(.274)	(.064)	(.127)	(.202)	(.086)	(.093)
Common religion	.058	.148**	.281***	.045	.161**	.288***	.083**	−.019
	(.043)	(.067)	(.075)	(.033)	(.062)	(.075)	(.039)	(.020)
R^2	.27	.35	.35	.42	.45	.42	.36	.26

Commonality controls	X	X	X	X	X	X	X	X
Distance controls	X	X	X	X	X	X	X	X
Composer fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World
	C. Effects of Connection on Similarity: Controlling for Religion of Either Composer (N = 23,489)							
Connected	.136**	.317***	.338***	.117***	.211***	.277***	.190***	.145***
	(.053)	(.091)	(.109)	(.039)	(.062)	(.089)	(.057)	(.045)
Catholic	.255***	.512***	.525***	.240***	.484***	.569***	.345***	.058***
	(.025)	(.038)	(.040)	(.010)	(.020)	(.033)	(.016)	(.012)
Protestant	.332***	.564***	.564***	.441***	.606***	.624***	.321***	.171***
	(.025)	(.037)	(.039)	(.012)	(.022)	(.033)	(.020)	(.016)
Jewish	−.049***	−.074***	−.124***	−.041***	−.136***	−.131***	−.004	−.033***
	(.009)	(.016)	(.020)	(.008)	(.016)	(.019)	(.019)	(.012)
R^2	.31	.34	.31	.40	.41	.35	.31	.21
Commonality controls	X	X	X	X	X	X	X	X
Distance controls	X	X	X	X	X	X	X	X
Composer fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

NOTE.—In panel A, the dependent variable is a dummy for whether the composer has an occupation listed in *Grove* as teacher (col. 1), a dummy for whether the composer taught another BM composer (col. 2), the number of BM students (col. 3), a dummy for whether the composer studied with another BM composer (col. 4), the number of BM teachers (col. 5), and a dummy for whether the pair of composers is connected (col. 6). Controls not shown in cols. 1–5 include dummies for century and continent of birth of the composer. Controls not shown in col. 6 include dummies for common birth country, time period, and their interaction; common nationality; and common descent. "Catholic," "Protestant," and "Jewish" are dummy variables that indicate the religious denomination of a composer; the benchmark is nonreligious composers. "Common religion" indicates pairs of composers who have a religious denomination in common. In panels B and C, the dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key, and time signature (cols. 4–8, respectively). "Connected" indicates realized teacher-student pairs. Controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. The data were collected by the authors (see sec. IV and app. D4 for details.).

* $p < .1$.
** $p < .05$.
*** $p < .01$.

D5. Studying Music versus Studying Composition

For musicians, "to study with" someone is a complex matter. All composers, after all, were musicians, and indeed many of them made their living performing music (and teaching music to amateurs), and so one could wonder whether studying with a great composer actually transmitted the skills (and styles) of composition or was just about how to play an instrument. In other words, studying piano with a great composer who was also a great pianist may have had little to do with composition and everything to do with playing the instrument. In this case, our coefficients on stylistic influence of the teacher would be biased toward zero. The true teacher influence on the compositional style of the student would be greater. Furthermore, it must be pointed out that this concern would be irrelevant if our data captured only those who studied composition. Therefore, in this section, we discuss, assess, and test the reliability of the realized teacher-student connections.

First of all, it has to be highlighted that each of the individuals covered in our research was a composer, be it alone for the fact that they composed meaningful enough works to be included in the BM dictionaries of musical themes. It is also conceivable that even if the teacher taught piano to the student but they were both composers, they talked about composing during their piano lessons. It is thus likely that influence of composition style was transmitted even if the teaching was primarily focused on something else.

Second, it is evident that Pfitzinger has aimed to list connections between composition teachers and students, as opposed to, for example, connections between two music performers. The aim becomes apparent from the title (*Composer Genealogies: A Compendium of Composers, Their Teachers, and Their Students*) and the preface:

> It is my hope that this book may serve as a resource for music historians, composers, and theorists who want to analyze the pedagogical influences of particular composers on their students. . . . [T]here is a noticeable dearth of information about composers teaching composers and the importance of examining compositional lineage. . . . As writers and researchers examine the relationships of composers, they will be able to more readily access the composition teachers that a particular composer had, [and] who taught those teachers. (Pfitzinger 2017, preface)

We proceed to test the Pfitzinger data using our own data from *Grove* on connections between composition teachers and students.[25] For this reason we reestimate the baseline regressions using only our own data from *Grove* on realized pairs of composition teachers and students. The results remain, in general, consistent with the baseline, but the coefficients are estimated with higher precision

[25] We collected our data independently from Pfitzinger and before he published his volume. In our data collection, we identified 32 realized pairs that Pfitzinger did not find (after checking on these, we are confident that our matches are correct). On the other hand, Pfitzinger has identified 45 realized pairs that we have not found in *Grove*. We have also checked on these pairs and concluded that *Grove* does not provide any mention of these connections. When reading other, more specialized reference works, we have been able to confirm some of these 45 realized connections. Since we have no reason to believe that there are mistakes in Pfitzinger, in the baseline specification we use the union of realized pairs that are found in either set (our *Grove* data or Pfitzinger).

and have a marginally greater magnitude, compared with the baseline (not reported). This could suggest that Pfitzinger may have overidentified some teacher-student relationships or included connections that were not very meaningful.

Finally, we conduct tests using occupation information from *Grove* in order to provide a better understanding of the difference between the influence of a composition teacher and that of a teacher of instrumental music. The composers covered in this research had up to six occupations listed in *Grove*, but more than 90% of composers had at most three occupations (see further details in app. E5). The most common instrumental occupation of the teacher is pianist (14%), followed by violinist (9%) and organist (5%).

We present the results in table D8 as follows: we exclude teachers who are pianists (panel A), exclude teachers who have one of the three most common instrumental occupations (i.e., pianists, violinists, or organists; panel B), exclude teachers who have any instrumental occupation that appears more than once (in total, there have been 11 unique instrumental occupations, and after this restriction our sample decreased by 99 teachers; panel C), keep teachers whose first (the main) occupation is that of a composer (panel D), and keep teachers whose only occupation is composers (panel E).

Throughout this increasingly restrictive sampling procedure, it becomes apparent that the "purer" the background of a composer teacher, the more influential he is on the compositional style of the student. In particular, the coefficients remain very stable in statistical significance, but they tend to increase in size throughout the subsampling.

It is not clear what determines this pattern, which could be due to several different factors. One possibility is that, during training, certain teacher-student pairs have also been discussing non–composition-related topics (e.g., how to play an instrument). Another one is that a teacher who is also an instrumentalist, and hence a performer, is more time constrained and can dedicate fewer resources to a single student.

TABLE D8
Effects of Connection on Similarity: Excluding Teachers of Instrumental Music

	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
	A. Exclude Teachers Who Are Pianists (N = 19,603)							
Connected	.126*	.281**	.304**	.126***	.204**	.269**	.224***	.150***
	(.065)	(.116)	(.140)	(.046)	(.079)	(.111)	(.059)	(.051)
R^2	.31	.33	.29	.36	.37	.33	.29	.22
	B. Exclude Teachers Who Are Pianists, Violinists, or Organists (N = 17,832)							
Connected	.153**	.360***	.403***	.137***	.221**	.305**	.262***	.165***
	(.073)	(.126)	(.151)	(.049)	(.086)	(.123)	(.061)	(.057)
R^2	.30	.32	.28	.36	.37	.34	.29	.22
	C. Exclude Teachers Who Have Any Instrumental Occupation (N = 17,524)							
Connected	.159**	.372***	.415***	.150***	.245***	.335***	.253***	.171***
	(.074)	(.127)	(.153)	(.048)	(.084)	(.123)	(.062)	(.058)
R^2	.30	.32	.28	.36	.37	.33	.30	.22
	D. Keep Teachers Who Are Mainly Composers (First Occupation; N = 18,848)							
Connected	.117**	.283***	.298**	.080**	.140**	.177*	.173***	.102**
	(.057)	(.097)	(.119)	(.040)	(.066)	(.091)	(.058)	(.042)
R^2	.29	.32	.29	.38	.39	.34	.30	.22

	E. Keep Teachers Who Are Only Composers (N = 9,779)							
Connected	.285**	.638***	.704***	.178**	.330***	.415**	.218***	.191**
	(.110)	(.199)	(.251)	(.072)	(.118)	(.182)	(.083)	(.080)
R^2	.32	.34	.30	.40	.40	.35	.32	.23
	Specifications							
Commonality controls	X	X	X	X	X	X	X	X
Distance controls	X	X	X	X	X	X	X	X
Composer fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

Note.—The point estimates presented are based on eq. (2). The dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key, and time signature (cols. 4–8, respectively) for a given pair of composers. "Connected" indicates realized teacher-student pairs. The reference group is conditioned to pairs in which the candidate teacher was alive for at least 1 year when the candidate student was between the ages of 5 and 30 and as outlined in each panel title. Controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. Standard errors are clustered by candidate teacher. The data were collected by the authors (see sec. IV for details).

* $p < .1$.

** $p < .05$.

*** $p < .01$.

Appendix E

Additional Results

E1. Other Direct Influences

Another form of direct influence is that of peers. Many composers formed peer connections with other contemporaneous composers and were exposed to their ideas and compositional style, which in turn may have influenced their own style. In this case, the similarity of the benchmark pairs of composers, if it included peer connections, would increase. This, in turn, would bias the coefficients on similarity of realized teacher-student pairs downward. In other words, our coefficients on teacher influence would be biased toward zero, whereas the true teacher effect would be greater than observed.[26]

To better understand and account for the bias arising from peer influence, we have collected extensive data from *Grove* on peer connections (i.e., connections between two music composers who made acquaintance during their lives). For our sample of composers, we have identified, in total, 3,050 connections between one of our 341 BM composers and any other composer (i.e., including composers not included in the BM sample). Among those 3,050 connections, there are 359 peer connections between two composers who are both included in our BM sample. Since *Grove* provides information on only significant events in a composer's life, the identified connections can be assumed to be meaningful or formative in some way.

The data on realized peer connections are then used in regressions summarized in table E1, as follows. First, we show the baseline model that excludes peer connections from the benchmark group (panel A; also table 2). Second, we keep peer connections and show that this marginally decreases the coefficients on teacher influence, as hypothesized above (panel B). Despite the downward bias, however, it is encouraging to observe that teacher influence is strong enough to deliver statistically significant and comparable (in size) coefficients for the whole sample.

These explorations suggest that a teacher's influence is independent and largely unaffected by a composer's exposure to peers. The tests show also that the results based on the baseline model and presented in table 2 are not sensitive to the exclusion of peer connections from the benchmark group.

[26] In theory, some composers may have been influenced by contemporaneous unconnected composers. We regard this is as a low-probability concern, especially for the earlier years, when access to information was restricted and costly. However, if this was the case, the influence of unconnected contemporaneous composers would lead to the same downward bias of the coefficients on teacher influence, as discussed above.

TABLE E1

EFFECTS OF PEER CONNECTION ON SIMILARITY

	PERCENT SHARED			COSINE SIMILARITY				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
	A. Baseline (Peer Connections Excluded; N = 23,489)							
Connected	.118**	.283***	.305***	.095**	.178***	.241***	.169***	.137***
	(.054)	(.092)	(.111)	(.039)	(.064)	(.091)	(.057)	(.045)
R^2	.29	.32	.28	.37	.38	.33	.29	.21
	B. Alternative Estimation (Peer Connections Not Excluded; N = 23,807)							
Connected	.101*	.255***	.274**	.086**	.156**	.211**	.160***	.131***
	(.054)	(.094)	(.113)	(.039)	(.065)	(.092)	(.058)	(.045)
R^2	.29	.32	.29	.38	.38	.33	.29	.21
	Specifications							
Commonality controls	X	X	X	X	X	X	X	X
Distance controls	X	X	X	X	X	X	X	X
Composer fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

NOTE.—The point estimates presented are based on eq. (2). The dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key, and time signature (cols. 4–8, respectively) for a given pair of composers. "Connected" indicates realized teacher-student pairs. The reference group is conditioned to pairs in which the candidate teacher was alive for at least 1 year when the candidate student was between the ages of 5 and 30. Controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. Standard errors are clustered by candidate teacher. The data were collected by the authors (see sec. IV for details).

* $p<.1$.

** $p<.05$.

*** $p<.01$.

E2. Influence of Past Masters

The influence of some great masters is likely to persist beyond their lifetime. For example, the looming shadow of Ludwig van Beethoven's genius has intimidated numerous composers who followed him. Besides Johannes Brahms, composers such as Felix Mendelssohn and Gustav Mahler felt Beethoven's presence. Mendelssohn also played a pivotal role in popularizing and reigniting interest in the work of Johann Sebastian Bach. It is important to note that none of the influences by past composers matter directly for the results of the paper, since the baseline estimations restrict the comparison group to contemporaneous composers (see sec. V.B and also app. D1). In other words, the influence of a deceased composer on a composer alive, such as that of Beethoven on Brahms or Bach on Mendelssohn, will not be directly observed in our specifications. However, there exist channels by which a past master may matter for our results—we discuss and address these concerns more rigorously in what follows.

The influence of past masters on current composers can hypothetically take one of the following three forms. First, masters do not influence the next generation(s). Second, masters influence every single composer in the next generation(s). Third, masters influence some, but not all, composers. The first two types of influence (influencing nobody or everybody) would not matter for our estimations, which look at differences between connected and unconnected contemporaneous composers. The third type of influence would be a problem, but only if masters influenced both the teacher and the student independently but nobody else. In other words, if masters influenced connected composers but not unconnected ones, then we would observe higher similarity between the teacher-student pairs relative to unconnected contemporaneous composers. As a result, the hypothetical past-master bias would increase the coefficients in our favor. For this bias to emerge, it is necessary that the past-master influence affects both teacher and student independently. Otherwise, for example, if the student was influenced by the past master via his teacher, then we would have an example of "teacher influence."

It is difficult to think of any plausible reason why past masters would systematically and independently influence the teacher and student but nobody else; hence, this matter should largely be regarded as theoretical. Nonetheless, we approach the problem more rigorously by estimating the past-master effect on all composers and separate out the past-master effect on those composers who—in our data set—have been in a realized teachers-student pair. In other words, what is estimated is the differential effect that past masters have on realized teachers or students. It is not clear ex ante how to determine a past master, but we have pursued a number of approaches based on top scores of the Murray quality index, the number of Spotify followers, the Spotify popularity score, or the length of the biographical entry in various sections. The results that follow are not sensitive to the choice of any particular quality measure or the cutoff value.

Table E2 highlights that composers tend to be more similar to important past composers—this does not come as a surprise. More importantly, the past-master effect is not larger for realized teacher-student pairs, but—if anything—it appears to be lower. It is encouraging to observe that there is no support for the past-master influence being greater for realized teacher-student pairs than for unconnected composers.

TABLE E2

PAST-MASTER EFFECT ON ALL COMPOSERS VERSUS THAT ON TEACHERS OR STUDENTS (N = 45,736)

	PERCENT SHARED			COSINE SIMILARITY				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
Past-master influence	.227**	.740***	.902***	.557***	1.072***	1.407***	.668***	.175*
	(.095)	(.094)	(.084)	(.039)	(.087)	(.173)	(.058)	(.103)
Past-master influence on teachers or students	−.094	−.190**	−.242**	−.072	−.137	−.277*	−.104	.015
	(.062)	(.079)	(.103)	(.047)	(.084)	(.166)	(.067)	(.111)
R^2	.34	.39	.35	.48	.49	.42	.30	.28
Commonality controls	X	X	X	X	X	X	X	X
Distance controls	X	X	X	X	X	X	X	X
Composer fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

NOTE.—The dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key, and time signature (cols. 4–8, respectively) for a given pair of composers. "Connected" indicates realized teacher-student pairs. A past master is identified as a composer with a Murray index higher than 15. Controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. Standard errors are clustered by candidate teacher. The data were collected by the authors (see sec. IV for details).

* p <.1.

** p <.05.

*** p < .01.

E3. Within-City Similarity

Through the centuries covered in this research, the city was an important defining unit for society, the economy, and culture. It is thus not surprising that composers were located almost exclusively in cities (see O'Hagan and Borowiecki 2010), especially since they needed to access large, expensive cultural infrastructure, such as concert halls and opera houses, in order to test and perform their works, and these are available only in cities. Therefore, one may want to restrict the sample to pairs of composers in which both teacher and student were located in the same city at the same time. This approach, which effectively decreases the actual geographic distance between two composers to about zero, is pursued in this section.

To conduct this analysis, we extract from *Grove* the lifetime migration records for each composer, including the dates when a stay in a city began and ended. Migration histories have been fairly well documented, since they form an important part of a person's biography. It is true that a few observations may be imprecise when it comes to the exact beginning/ending date, but there are no indications for the existence of any systematic biases.

The data collection effort resulted in 2,117 composer-city-level observations. Out of these, we dropped 108 observations, in which the exact location is not provided but only the country (e.g., "Germany (city unknown)") or when multiple places were visited (mostly during touring in another country or continent, e.g., "Various, mult. countries (Europe; Russia)"). The remaining observations indicate that composers were located, on average, in 6.05 cities during their lifetime, including the city of birth and returns to the same city. The most mobile composers visited up to 20 cities during their lifetime, with a maximum of 23 cities. There are 149 unique cities in our data, with Paris being the most prominent one (10,153 pairs, unconditioned, realized, or unrealized), followed by London (2,700), Vienna (2,346), Berlin (1,539), Rome (1,275), and New York City (990).

We condition to pairs of composers who overlapped in a city (i.e., realized/candidate teacher and realized/candidate student were located in the same city at the same time). We also keep the baseline condition requiring that the teacher was alive when the student was in his formation age (between 5 and 30); this restriction is not required to obtain the same results qualitatively, but it serves the purpose of our estimations. Both conditions ultimately mean that we compare the similarity of connected composers with the similarity of unconnected composers, contemporaneously and within the borders of the same city. Accordingly, this estimation also mitigates the concern of location-specific indirect influences (see sec. V).

Table E3 shows the results for the regression that is conditional on city overlap during the student's formation age and includes city fixed effects in addition to all previous controls. Some of the point estimates are found to be slightly smaller in comparison with the baseline, as expected, but more importantly, the correlation between connection and similarity is positive and statistically significant.

TABLE E3

EFFECTS OF CONNECTION ON WITHIN-CITY SIMILARITY (N = 5,622)

	PERCENT SHARED			COSINE SIMILARITY				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
Connected	.180	.383***	.456***	.138***	.222***	.273**	.155**	.115**
	(.117)	(.090)	(.075)	(.036)	(.056)	(.119)	(.060)	(.048)
R^2	.38	.40	.37	.44	.44	.39	.35	.31
Commonality controls	X	X	X	X	X	X	X	X
Distance controls	X	X	X	X	X	X	X	X
Composer fixed effects	X	X	X	X	X	X	X	X
City fixed effects	X	X	X	X	X	X	X	X
Sample	World	World	World	World	World	World	World	World

NOTE.—The dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key, and time signature (cols. 4–8, respectively) for a given pair of composers. “Connected” indicates realized teacher-student pairs. The reference group is conditioned to pairs of composers who overlapped in a city (i.e., realized/candidate teacher and realized/candidate student were located in the same city at the same time) and in which the candidate teacher was alive for at least 1 year when the candidate student was between the ages of 5 and 30. Controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. Standard errors are clustered by candidate teacher. The data were collected by the authors (see sec. IV and app. E3 for details).

** $p < .05$.

*** $p < .01$.

E4. Competition and the Formation of Teacher-Student Connections

The analysis of how competition matters for the originality of a composer, as we have seen in section IX, raises the question of whether competition among composers matters for the probability of forming a teacher-student connection. To approach this question, we reuse the subsample and setup from the previous estimations and, in table E4, regress the variable Connected on the logged number of composers located in the same city (col. 1) and on the logged number of composers located in the same city at the same time (col. 2). The coefficients are estimated with moderate precision and indicate that with higher competition, it becomes marginally less likely to form a connection with a teacher. It is possible that in competitive environments, the focus on giving (or receiving) training is limited.

These estimations are complemented by the addition of the ratio of prospective teachers or students among composers located in the same city at the same time. The ratio is calculated by dividing the number of potential teachers (i.e., composers who were at some point in life a teacher to another composer in our sample) over the total number of composers covered in our sample and located in the same city at the same time. The ratio of students in the same city and time is obtained in an analogous way. The results are presented in column 3. Column 4 includes, in addition, the logged number of composers located in the same city at the same time. As one would expect, with a greater ratio of potential teachers or students, the probability of connecting increases.

TABLE E4
Effects of Competition on Connection (N = 5,766)

	Connected			
	(1)	(2)	(3)	(4)
No. of composers in same city (logged)	−.00405*			
	(.00211)			
No. of composers in same city and time (logged)		−.00355*		−.00652**
		(.00194)		(.00273)
Teacher ratio			.0431**	.0442**
			(.0193)	(.0204)
Student ratio			.0349*	.0581**
			(.0200)	(.0235)
R^2	.160	.160	.161	.163
Commonality controls	X	X	X	X
Distance controls	X	X	X	X
Composer fixed effects	X	X	X	X
Sample	World	World	World	World

Note.—The dependent variable Connected indicates realized teacher-student pairs, and it is regressed on the logged number of composers located in the same city (col. 1), the logged number of composers located in the same city in the same decade (col. 2), and ratios of prospective teachers or students among composers located in the same city in the same decade (cols. 3 and 4). "Teacher ratio" is calculated by dividing the number of prospective teachers (i.e., composers who were at some point in life a teacher to another composer in our sample) by the total number of composers covered in our sample and located in the same city and the same decade. "Student ratio" is obtained in an analogous way. The reference group is conditioned to pairs in which the candidate teacher was alive for at least 1 year when the candidate student was between the ages of 5 and 30 and to composer pairs (whether realized or unrealized) that overlapped in a city. Controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. Standard errors are clustered by candidate teacher. The data were collected by the authors (see sec. IV for details).
* $p<.1$.
** $p<.05$.

E5. Effects of Connection on Similarity in Occupation, Musical Instrument, and Musical Form

This paper provides efforts to illuminate the phenomenon of diffusion and influence by teachers in music composition. The focus is on how the teacher shapes the student's style of work, since this comes closest to the concept of an idea and its transmission. Another way in which the teacher potentially influences the student is by providing them with the right tools and methods, for example, by explaining how to compose for the organ, as opposed to for an orchestra. This section provides an exploration of these other influences by looking at nonthematic material, in particular composers' lists of occupations and choice of musical instruments and musical forms.

There is another advantage of this approach, especially if one is concerned that the compositional style of a musician changes over the life cycle. The approach pursued here diminishes this concern, since it is based on measures that vary considerably less over a composer's lifetime. For example, it is most unlikely that a composer who is a pianist will become a violinist (at least not a violinist of a high enough quality to be mentioned in *Grove*) because of external influences. It would also be a big undertaking for a composer who, for example, writes predominantly for the piano to begin composing for the flute or for an opera composer to begin writing chamber music. In short, the entrance barriers across occupations or musical instruments and forms are considerably greater than tweaks in the compositional style.

Before we present the results, a few words are needed on the additional collection of data and its summary.

E5.1. Additional Data Collection on Nonthematic Output

First, we collect for each composer lists of occupations from *Grove*, which are systematically provided at the beginning of each biography. For example, Fryderyk Chopin was a "Polish composer and pianist." It was most common for composers covered in our sample to have one occupation only (45%), followed by two occupations (28%, as in the example above), three occupations (18%), and so on; only one composer had six occupations. The most common occupation was obviously that of a composer, which sees no variation, followed by conductor (18%), pianist (14%), teacher (13%), violinist (9%), and organist (5%). The list of occupations is typically provided in the order of significance, and hence, not surprisingly, the most common first occupation is that of a composer (89%), followed by violinist and pianist (about 2% each).

Second, we collect data on the musical instrument and musical form of each composition. We are able to extract this information from the BM dictionaries of musical themes. For example, one of Beethoven's works is described as follows: "Concerto No. 1, in C, Op. 15, Pft.," which enables us to identify the musical form (concerto) and musical instrument (fortepiano). We are able to identify the instrument(s) for 79% of the works covered, which is a high proportion. The most common musical instrument is the fortepiano (32% of works per composer), followed by orchestra (21%), violin (14%), string (7%), harpsichord (6%), organ (1.6%), cello (1.5%), and flute (1.4%).[27] Using the available information, we construct a dummy variable that indicates a composer's *main instrument*, which we simply define as the mode of all instruments provided for a composer. The main instrument is fortepiano (39% of composers), followed by orchestra (31%), violin (13%), harpsichord (7.5%), and organ and flute (1.5% each).

Third, we obtain data on musical forms, which are available for 61% of works. These records are noisy and contain as many as about 200 unique entries (after

[27] Two side remarks are in order. First, the missing instruments in the unclassified themes is not a problem of data quality in the source dictionary but rather a reflection of the fact that composers have not always indicated the target (or preferred) instrument. Second, orchestra is an aggregate that combines instruments from different families of musical instrument, typically including some of the separately listed instruments (e.g., violin), but not all (e.g., organ). In the results that follow, orchestra is treated on a par with the individually listed instruments, since it captures some of the choices or preference of the composer. However, the results would remain consistent if the orchestra category was instead excluded. Analogous observations apply also for the string family of instruments.

corrections for spelling and translations), but only 19 musical forms appear more often than 0.5% of the time (symphony, suite, overture, concert, etc.). The results that follow remain consistent whether one focuses on the 19 most common musical forms or aggregates all observations into categories, such as concert, chamber, theatrical, dance, church, and improvisations.[28] The main aggregated musical forms (the mode of all musical forms of a composer) are concert music (34%), theatrical (25%), and chamber (20%).

The newly collected data can then be used to illuminate how often pairs of composers have a particular attribute in common. A simple inspection of averages of common attributes delivers insightful patterns.

1. Any instrumental occupation (pianist, violinist, etc.) has only 3% of all pairs of composers in common but as many as 9.9% of realized pairs (i.e., teacher and student were actually connected).
2. Any musical instrument (piano, violin, etc.) has 26% of all pairs of composers in common and 51% of realized pairs.
3. Any musical form (grouped into concert, chamber, etc.) has 72% of all pairs of composers in common and 86% of realized pairs (looking at musical forms in a disaggregated way, we would have, respectively, 66% and 80%).

E5.2. Results on Nonthematic Similarity

There are different ways to identify the problem at hand (in fact, there is probably enough material here for a separate study). In an attempt to keep the paper as methodologically coherent and consistent as possible, we simply regress the newly constructed commonality terms on the dummy variable Connected that identifies realized pairs and include the same controls as in the baseline regressions, namely, the sets of distance variables and commonality controls, and condition to pairs of composers in which the older of the two composers in a pair was alive for at least 1 year while the younger was between the ages of 5 and 30.

The results are presented in table E5. We show how connection matters for similarity in the occupation of teacher and student (panel A), similarity in choice of musical instruments (panel B) or musical forms (panel C), and how a student's choice of musical instruments depends on the teacher's main instrument or the teacher's instrumental occupation (panel D). Throughout these results, we observe consistently that connection matters for any of the measures. For example, realized pairs are 5% more likely to have an instrumental occupation in common (e.g., both the teacher and the student are pianists; col. 1, panel A). We also show that this effect persists for any of the instrumental occupations that involve an instrument from the keyboard instrument family (col. 2), or the piano (col. 3), and even for noninstrumental occupations (e.g., occupations such as teacher, theorist, or writer; col. 4). Throughout the results summarized in panels A–C, it

[28] Another word of caution: categorization of works is difficult to conduct in a systematic way, since certain works could belong to one or more of the suggested aggregated musical forms.

becomes apparent that common attributes, whether a common occupation, musical instrument, or musical form, are about 5%–17% more likely to be observed for realized pairs.

Finally, we also disclose that a student composes about half a work more (or 6 percentage points more works) for an instrument that is his actual teacher's main instrument (cols. 1 and 2, panel D). The student also composes significantly more for an instrument that is his teacher's occupational instrument (e.g., student writes more for the piano if the teacher is a pianist; cols. 3–4, panel D). There are also many other interesting indications of the teacher's influence (not reported). For example, students have significantly more students of their own if their teacher has an occupation as teacher.

It is important to note that the baseline results on the effects of connection on similarity are robust to the inclusion of any of the commonality controls obtained and analyzed in this section (not reported). See also, for example, table D8 on estimations that exclude teachers of instrumental music.

TABLE E5
Effects of Connection on Similarity in Occupation, Musical Instrument, and Musical Form

	(1)	(2)	(3)	(4)
	A. Common Occupation (N = 23,489)			
	Common Any Instrumental Occupation	Common Keyboard Occupation	Common Pianist Occupation	Common Noninstrumental Occupation
Connected	.0506***	.0523***	.0481***	.0926***
	(.0179)	(.0177)	(.0169)	(.0223)
R^2	.149	.167	.158	.193
	B. Common Musical Instrument (N = 23,489)			
	Common Any Instrument	Common Main Instrument	Common Keyboard	Common Piano
Connected	.175***	.0458**	.148***	.147***
	(.0307)	(.0214)	(.0295)	(.0299)
R^2	.298	.456	.292	.274
	C. Common Musical Form (N = 23,489)			
	Common Any Form	Common Main Form	Common Concert Form	Common Chamber Form
Connected	.0846***	.0848***	.152***	.0674***
	(.0224)	(.0309)	(.0290)	(.0227)
R^2	.416	.218	.251	.209

TABLE E5 (*Continued*)

	(1)	(2)	(3)	(4)
	D. Student's Instrument Choice Based on Teacher's Main or Occupational Instrument			
	Student's Choice of Teacher's Main Instrument		Student's Choice of Teacher's Instrumental Occupation	
	Count	Share	Count	Share
Connected	.548**	.0662***	.308***	.0385***
	(.225)	(.0224)	(.116)	(.0144)
Observations	20,816	19,064	22,320	21,546
R^2	.248	.142	.147	.137
	Specifications			
Commonality controls	X	X	X	X
Distance controls	X	X	X	X
Composer fixed effects	X	X	X	X
Sample	World	World	World	World

Note.—The point estimates presented are based on an adaptation of eq. (2). The dependent variable indicates pairs of composers who have a common occupation (panel A), a common musical instrument (panel B), or a common musical form (panel C) or pairs in which the student composes for an instrument that is his teacher's main instrument or occupational instrument (panel D). "Connected" indicates realized teacher-student pairs. The reference group is conditioned to pairs in which the candidate teacher was alive for at least 1 year when the candidate student was between the ages of 5 and 30. Controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. Standard errors are clustered by candidate student. The data were collected by the authors (see app. E5 for details).

** $p < .05$.

*** $p < .01$.

E6. Implications of Class, Wealth, and Employer on Educational Involvement

The lives and work of composers have been part of wider ecosystems and hence have been likely influenced by social, economic, and political developments. We explore here how a composer's class, wealth, or type of employer—in particular whether the composer is working for royals or for the church—matters for various outcomes, including the probability of becoming a teacher or connecting with others.

There are a number of obvious limitations on the availability of systematic, comparable, and reliable data on a person's class or wealth in history. However, we are once again fortunate to have access to detailed biographical entries from which we can obtain some valuable indicators. In particular, from *Grove* we obtain records on family background, which we then use to assign a social class (upper, middle, or lower) to each individual. We also collect information that allows us to approximate the family wealth status of some composers.

We are able to identify the social class in 271 (out of 341) cases from biographical entries in *Grove*. The upper class accounts for 9% of this subsample (described in *Grove* as "aristocratic," "noblemen," "gentry," etc.; in a few rare cases, the class is deduced from descriptions of the ownership of significant properties). With 86%, the middle class accounts for the bulk of the subsample, and it is mostly classified according to the occupation of the father, who was most often a musician (23%), followed by public servant (6%), merchant (6%), artist (5%), doctor or pharmacist (3%), or craftsman (2%).[29] The lower class accounts for 4.8% (described in Grove as "farmer" or somebody "extremely modest," etc.).

Second, we have coded the family background as wealthy (described in *Grove* as "wealthy," "prosperous," "well-to-do," etc.) for 45 composers and as poor (described as "humble," "extremely modest," "impecunious," etc.) for 16 composers.[30] With only 61 observations on the wealth status, we certainly miss out on a large number of composers. However, since *Grove* provides only significant information, one could speculate that the bias from missing this information is not particularly meaningful: biographies that do not contain information on the composer's wealth status were possibly cases in which the wealth is unremarkable, or "average."

Third, we have collected additional data from *Grove* on the employers of composers. These data are provided frequently and often in connection with mobility, and they enabled us to identify 93 instances where the composer was working for royals, including the tsar, king, prince, queen, princess, count, royal family, or duke. There are also 69 instances where the composer is employed by the church, usually as an organist (to compose and perform) or choirmaster at a cathedral, church, or basilica, or, in two cases, by the pope (Josquin des Prez and Girolamo Frescobaldi). Other composers have been employed by cultural or educational institutions, influential families, unspecified employers, or outside music.

We explore how a composer's background matters for his involvement with teaching or studying and summarize the findings in table E6. The following five dependent variables are considered: a dummy variable for whether the composer has an occupation listed in *Grove* as a teacher (col. 1), a dummy for whether the composer taught another BM composer (col. 2), the number of BM students (col. 3), a dummy for whether the composer studied with another BM composer (col. 4), and a given composer's number of BM teachers (col. 5).

The results are presented for social classes (panel A), wealth (panel B), and royal versus church employers (panel C). The point estimates on class are statistically insignificant. Wealthy composers appear to be less likely to have a teacher occupation in *Grove* or less likely to be teaching other BM composers and more likely to study with other BM composers.[31] Composers employed by the church have a higher probability of teaching other BM composers and a higher number

[29] Some of these occupations could nowadays be regarded as upper class (e.g., some doctors), but historically the upper class was usually seen as a group consisting of aristocrats, ruling families, and titled people.

[30] In few additional biographies the financial status of a family is mentioned, but the information provided points neither to a wealthy nor to a poor background (e.g., described as "comfortable"). These observations are kept on a par with the unobserved ones.

[31] This estimation has to be interpreted with caution, however, since it builds on very few observations. Furthermore, it is based on an extreme approach in which we compare wealthy composers with poor composers. The significance of the estimations would disappear if we instead compared wealthy or poor composers with all other composers (i.e., those with an unremarkable wealth).

of BM students. This could be a reflection of the historical focus of the church on music education (see historical context in sec. 3).

Furthermore, we analyze whether there are any differences in the probability of forming a teacher-student connection based on having class, wealth, or type of employer in common. It can be seen in column 6 of table E6 that the commonality controls are estimated mostly with a negative sign and, in a few cases, even turn statistically significant. This may indicate that teacher-student relationships are, at least to some degree, formed also across composers of different backgrounds and independently from the type of employer, or perhaps even unaffected by the political system more in general.[32] This is an interesting indication that matching may have taken place across social boundaries.

In relation to the baseline results of the paper, the absence of any clear patterns when it comes to the formation of educational connections is an encouraging finding.

[32] The results would be comparable if, instead, we controlled explicitly for a teacher's employer (e.g., royals vs. church vs. other employers) or for whether either the teacher or the student was employed by royals or the church.

TABLE E6

EFFECTS OF CLASS, WEALTH, AND EMPLOYER ON EDUCATIONAL INVOLVEMENT AND CONNECTION

	Teacher Occupation (1)	Realized Teacher (2)	No. of Students (3)	Realized Student (4)	No. of Teachers (5)	Connected (6)
	A. Upper/Middle versus Lower Social Class					
Upper class	−.143	−.266	−.283	.145	.180	
	(.124)	(.164)	(.598)	(.168)	(.307)	
Middle class	−.0828	−.183	−.676	−.135	−.135	
	(.101)	(.134)	(.489)	(.137)	(.251)	
Common any class						−.00224
						(.00223)
Observations	266	266	266	266	266	14,296
R^2	.006	.020	.027	.037	.015	.062
	B. Family Wealth Status at Composer's Birth					
Wealthy (vs. poor)	−.189*	−.333**	−.458	.295*	.227	
	(.0950)	(.127)	(.843)	(.156)	(.280)	
Common wealth status						−.0151**
						(.00720)
Observations	59	59	59	59	59	794
R^2	.090	.122	.026	.065	.013	.074
	C. Type of Employer: Royals versus Church					
Employed by royals	−.0568	.0329	−.0752	−.116	−.198	
	(.0595)	(.0768)	(.269)	(.0836)	(.146)	
Employed by church	.0311	.285***	.659**	.134	.193	
	(.0661)	(.0854)	(.299)	(.0929)	(.162)	
Common royals employer						−.00587
						(.00643)
Common church employer						.00883
						(.0135)
Observations	341	341	341	341	341	23,489
R^2	.004	.043	.026	.013	.009	.055
	Specifications					
Century fixed effects	X	X	X	X	X	
Continent fixed effects	X	X	X	X	X	
Commonality controls						X
Distance controls						X

TABLE E6 (*Continued*)

	Teacher Occupation (1)	Realized Teacher (2)	No. of Students (3)	Realized Student (4)	No. of Teachers (5)	Connected (6)
Composer fixed effects						X
Sample	World	World	World	World	World	World

NOTE.—The dependent variable is a dummy for whether the composer has an occupation listed in *Grove* as a teacher (col. 1), a dummy for whether the composer taught another BM composer (col. 2), the number of BM students (col. 3), a dummy for whether the composer studied with another BM composer (col. 4), the number of BM teachers (col. 5), and a dummy for whether the pair of composers is connected (col. 6). Controls not shown in cols. 1–5 include dummies for century and continent of birth of the composer. Controls not shown in col. 6 include dummies for common birth country, time period, and their interaction; common nationality; and common descent. "Common any class," "Common wealth status," "Common royals employer," and "Common church employer" indicate pairs of composers who have, respectively, class, wealth, royal employer, and church employer in common. The data were collected by the authors (see sec. IV and app. E6 for details.).

* $p<.1$.
** $p<.05$.
*** $p<.01$.

We have also tried to pursue additional approaches to measure the financial situation of a composer. It is unfortunately not possible to obtain systematic data on earnings for a large number of composers. However, there are some rare records available that enable us to pursue two independent approaches. First, we considered a rare data series on the income of Mozart, available for the years from 1781 to 1791 (Baumol and Baumol 1994). Second, we obtained information on the intensity of financial (money-related) concerns expressed in written correspondence of a small group of composers. The data were previously used in a study on whether and how emotional factors matter for the creative output of composers (Borowiecki 2017).

Analyzing these data implies that a higher income or fewer money-related concerns correspond to lower similarity of composers and hence suggest higher originality. To put it differently, more creative output is produced in times when the financial situation of the composer is in a relatively good shape. However, since nothing can be said about causality and because of the very low number of observations, these explorations are neither reported nor pursued any further here.

E7. Stable Influence across Musical Periods

This research covers about five centuries of data, and the inclusion of time fixed effects, various subsampling approaches, or imposed restrictions will largely mitigate concerns arising from any potential time variation. However, one may wonder what are the differences, if any, in the extent of teacher influence over time. We approach this issue by looking at whether the degree of similarity differs over musical periods. The analysis is presented in table E7, where similarity is regressed on musical periods based on the student's year of birth, as follows: Renaissance (before 1600), which is the baseline, Baroque (1600–1750), Classical (1750–1830), Early Romantic (1830–60), and Late Romantic (after 1860).

The coefficients are mostly insignificant, which indicates that teacher-student similarity has remained fairly stable across musical periods. There is one exception, however: the key signature metric delivers smaller coefficients on similarity for all periods following the Renaissance, and this result is statistically significant from the Classical period (col. 7). Interestingly, this finding is in line with music historical developments. The key signature originated in the medieval period, but it was initially very simple, using only a one-flat signature. According to the *Harvard Dictionary of Music*, key signatures with more than one flat did not appear until the Baroque and signatures with sharps not until the Classical period. These historical developments increased composers' potential for differentiation with regard to key signature; our result reflects this by disclosing the decreasing similarity.

TABLE E7

Stable Influence across Musical Period ($N = 211$)

	Percent Shared			Cosine Similarity				
	2-Grams (1)	3-Grams (2)	4-Grams (3)	2-Grams (4)	3-Grams (5)	4-Grams (6)	Key (7)	Time (8)
Baroque	.013	.660	1.542	.436	.691	1.398	−.644	.207
	(.317)	(.655)	(1.162)	(.298)	(.671)	(.960)	(.583)	(.436)
Classical	−.388	.130	.274	.244	.110	−.214	−.830*	−.252
	(.258)	(.369)	(.586)	(.236)	(.497)	(.532)	(.443)	(.426)
Early Romantic	−.393	.081	.222	.151	.223	.117	−.736*	−.418
	(.245)	(.312)	(.539)	(.233)	(.484)	(.520)	(.437)	(.423)
Late Romantic	−.775***	−.453	−.268	−.242	−.415	−.529	−.942**	−.536
	(.258)	(.328)	(.555)	(.246)	(.496)	(.540)	(.449)	(.429)
R^2	.06	.06	.07	.13	.12	.14	.07	.09

Note.—The dependent variable is a standardized similarity coefficient that measures the percentage of collective 2-/3-/4-grams shared (cols. 1–3, respectively) or the cosine similarity of 2-/3-/4-grams, key signature, and time signature (cols. 4–8, respectively) for realized teacher-student pairs. The musical periods are based on the birth year of the student as follows: Renaissance (before 1600), which is the baseline, Baroque (1600–1750), Classical (1750–1830), Early Romantic (1830–60), and Late Romantic (after 1860). Controls not shown include dummies for common birth country, time period, and their interaction; common nationality; and common descent. Standard errors are clustered by candidate teacher. The data were collected by the authors (see sec. IV for details).

* $p < .1$.

** $p < .05$.

*** $p < .01$.

Appendix F

Teacher-Student Pairs

TABLE F1
List of Teacher-Student Pairs

			Percent Shared			Cosine Similarity				
Teacher	Student	Year Met	2-Grams	3-Grams	4-Grams	2-Grams	3-Grams	4-Grams	Key	Time
Adam, Adolphe	Délibes, Clément Leo	1847	.44	.22	.07	.85	.38	.14	.54	.84
Albeniz, Isaac	Séverac, Déodat de		.30	.08	.00	.39	.12	.00	.28	.59
Albeniz, Isaac	Turina, Joaquin		.46	.19	.07	.74	.43	.17	.33	.86
Arensky, Anton	Glière, Reinhold	1884	.28	.07	.00	.51	.13	.00	.22	.42
Arensky, Anton	Gretchaninov, Alexander	1882	.25	.08	.04	.58	.30	.07	.27	.21
Arensky, Anton	Juon, Paul		.31	.08	.03	.54	.14	.05	.43	.43
Arensky, Anton	Medtner, Nicolas		.26	.10	.00	.43	.19	.00	.43	.63
Arensky, Anton	Rachmaninov, Sergei	1885	.40	.13	.03	.66	.30	.08	.55	.81
Arensky, Anton	Scryabin, Alexander		.41	.12	.04	.64	.28	.10	.25	.87
Bach, Carl Philipp Emanuel	Bach, Johann Christian		.45	.19	.09	.78	.47	.25	.54	.93
Bach, Johann Christian	Mozart, Wolfgang Amadeus	1764	.35	.19	.08	.85	.65	.45	.85	.89
Bach, Johann Sebastian	Bach, Carl Philipp Emanuel	1714	.51	.21	.07	.81	.59	.33	.74	.87
Bach, Johann Sebastian	Bach, Johann Christian	1735	.36	.17	.06	.83	.57	.36	.76	.71
Bach, Johann Sebastian	Bach, Wilhelm	1710	.36	.10	.03	.87	.57	.35	.47	.94
Balakirev, Mily	Borodin, Alexander	1862	.37	.10	.03	.59	.25	.07	.54	.57
Balakirev, Mily	Cui, César	1856	.27	.11	.03	.48	.21	.06	.00	.46
Balakirev, Mily	Mussorgsky, Modest	1858	.33	.09	.02	.51	.24	.08	.31	.60
Balakirev, Mily	Rimsky-Korsakov, Nikolai	1861	.43	.10	.02	.64	.30	.05	.38	.65
Balakirev, Mily	Tchaikovsky, Piotr Ilich	1869	.36	.09	.03	.71	.33	.12	.58	.78
Bloch, Ernest	Jacobi, Frederick		.22	.06	.01	.52	.14	.03	.16	.63
Boieldieu, François-Adrien	Adam, Adolphe	1821	.47	.24	.08	.85	.38	.15	.24	.63
Boito, Arrigo	Wolf-Ferrari, Ermanno	1895	.55	.24	.07	.86	.69	.53	.56	.60
Brahms, Johannes	d'Albert, Eugen		.14	.04	.02	.43	.30	.22	.46	.78

Bruch, Max	Malipiero, Gian Francesco	1906	.52	.16	.02	.64	.24	.05	.32	.35
Bruch, Max	Respighi, Ottorino	1902	.56	.21	.07	.75	.45	.23	.41	.21
Bruch, Max	Straus, Oskar		.41	.15	.05	.59	.29	.15	.41	.14
Bruch, Max	Williams, Ralph Vaughan	1897	.54	.21	.07	.82	.61	.32	.64	.27
Bruckner, Anton	Kreisler, Fritz	1882	.41	.26	.12	.85	.64	.32	.41	.60
Bruckner, Anton	Schelling, Ernest		.26	.08	.03	.54	.26	.14	.00	.58
Buxtehude, Dietrich	Bach, Johann Sebastian	1705	.55	.17	.06	.83	.61	.36	.67	.84
Byrd, William	Morley, Thomas		.42	.14	.01	.62	.24	.07	.88	.53
Byrd, William	Weelkes, Thomas		.40	.12	.03	.52	.19	.05	.45	.43
Cannabich, Christian	Stamitz, Carl		.43	.13	.06	.58	.16	.11	.32	.63
Carissimi, Giacomo	Scarlatti, Alessandro		.50	.10	.01	.67	.19	.02	.13	.78
Chadwick, George	Still, William Grant		.24	.05	.00	.25	.04	.00	.00	.06
Cherubini, Luigi	Auber, Daniel	1805	.42	.18	.07	.69	.40	.18	.60	.56
Cherubini, Luigi	Boieldieu, François-Adrien		.52	.26	.10	.87	.46	.16	.78	.86
Cherubini, Luigi	Halévy, Fromental	1811	.38	.06	.00	.71	.17	.00	.18	.47
Clementi, Muzio	Field, John		.33	.14	.05	.54	.24	.09	.32	.46
Clementi, Muzio	Meyerbeer, Giacomo		.41	.15	.05	.65	.30	.14	.55	.82
Copland, Aaron	Bernstein, Leonard		.38	.13	.01	.65	.19	.01	.66	.92
Copland, Aaron	Harris, Roy	1926	.38	.14	.05	.80	.50	.18	.78	.36
Copland, Aaron	Schuman, William		.45	.12	.01	.76	.25	.01	.46	.41
Corelli, Arcangelo	Locatelli, Pietro		.41	.16	.08	.69	.39	.22	.00	.85
d'Albert, Eugen	Dohnányi, Ernő	1897	.31	.10	.01	.37	.06	.01	.00	.50
Debussy, Claude	Bartók, Béla		.57	.24	.06	.73	.46	.25	.65	.81
Délibes, Clément Leo	De Koven, Reginald		.28	.11	.03	.58	.24	.06	.64	.33
Délibes, Clément Leo	Kreisler, Fritz		.57	.34	.10	.86	.49	.15	.55	.88
Delius, Frederick	Warlock, Peter	1911	.47	.15	.02	.74	.33	.06	.35	.75
des Prez, Josquin	Janequin, Clement		.52	.22	.10	.79	.57	.26	.29	1.00
d'Indy, Vincent	Albéniz, Isaac	1895	.53	.25	.07	.66	.36	.12	.49	.87
d'Indy, Vincent	Auric, Georges	1914	.38	.14	.04	.68	.34	.08	.53	.61
d'Indy, Vincent	Canteloube, Joseph	1902	.38	.21	.09	.67	.41	.18	.58	.36
d'Indy, Vincent	Honegger, Arthur	1911	.56	.30	.11	.77	.51	.19	.47	.51
d'Indy, Vincent	Jongen, Joseph		.29	.06	.01	.55	.18	.06	.77	.74
d'Indy, Vincent	Lekeu, Guillaume	1890	.48	.17	.06	.76	.42	.17	.37	.52
d'Indy, Vincent	Milhaud, Darius		.61	.28	.08	.79	.47	.16	.30	.53

TABLE F1 (*Continued*)

Teacher	Student	Year Met	Percent Shared			Cosine Similarity				
			2-Grams	3-Grams	4-Grams	2-Grams	3-Grams	4-Grams	Key	Time
d'Indy, Vincent	Nin, Joaquín		.54	.28	.06	.60	.36	.14	.65	.90
d'Indy, Vincent	Roussel, Albert		.48	.13	.02	.61	.28	.02	.59	.75
d'Indy, Vincent	Satie, Erik	1905	.39	.15	.02	.71	.33	.04	.55	.84
d'Indy, Vincent	Séverac, Déodat de		.32	.09	.04	.65	.27	.12	.25	.56
d'Indy, Vincent	Turina, Joaquín		.56	.23	.07	.77	.44	.14	.67	.90
Dohnányi, Ernő	Bartók, Béla		.41	.17	.06	.73	.29	.10	.68	.79
Dukas, Paul	Chávez y Ramírez, Carlos		.13	.03	.02	.12	.04	.03	.32	.32
Dukas, Paul	Milhaud, Darius		.15	.04	.01	.45	.27	.10	.34	.23
Dukas, Paul	Piston, Walter		.20	.05	.01	.39	.17	.05	.37	.45
Dvořák, Antonin	Burleigh, Harry Thacker		.36	.14	.06	.79	.53	.20	.59	.58
Dvořák, Antonin	Friml, Rudolf	1895	.22	.05	.01	.61	.30	.06	.21	.59
Dvořák, Antonin	Lehár, Franz		.43	.20	.10	.76	.57	.31	.79	.75
Dvořák, Antonin	Suk, Josef	1891	.25	.09	.02	.65	.33	.11	.46	.58
Elgar, Edward	Carpenter, John Alden	1906	.43	.17	.06	.69	.40	.18	.47	.53
Enescu, George	Piston, Walter		.44	.18	.05	.69	.32	.07	.22	.58
Fauré, Gabriel	Aubert, Louis	1887	.31	.07	.02	.52	.16	.05	.07	.79
Fauré, Gabriel	Casella, Alfredo		.45	.18	.06	.84	.49	.15	.27	.52
Fauré, Gabriel	Enescu, George	1896	.45	.23	.10	.83	.58	.26	.28	.48
Fauré, Gabriel	Honegger, Arthur		.61	.30	.13	.89	.60	.28	.27	.76
Fauré, Gabriel	Ibert, Jacques		.49	.20	.06	.87	.47	.17	.27	.55
Fauré, Gabriel	Jongen, Joseph		.23	.05	.01	.53	.25	.10	.48	.68
Fauré, Gabriel	Messager, André	1871	.19	.06	.01	.57	.21	.03	.48	.33
Fauré, Gabriel	Ravel, Maurice	1897	.62	.33	.12	.91	.56	.20	.64	.83
Fauré, Gabriel	Schmitt, Florent	1889	.25	.10	.04	.59	.40	.21	.28	.81
Field, John	Glinka, Mikhail	1817	.33	.11	.03	.52	.17	.05	.20	.44
Franck, César	Bemberg, Henri		.23	.07	.02	.64	.28	.08	.30	.59
Franck, César	Chausson, Ernest		.61	.26	.05	.82	.46	.13	.52	.40
Franck, César	Debussy, Claude		.62	.31	.09	.80	.53	.19	.67	.75
Franck, César	Dukas, Paul		.22	.05	.01	.58	.25	.03	.32	.22

Franck, César	Duparc, Henri		.38	.14	.04	.72	.41	.14	.26	.84
Franck, César	Hüe, Georges		.27	.11	.02	.68	.37	.07	.35	.75
Franck, César	Lekeu, Guillaume	1889	.34	.11	.03	.63	.31	.07	.15	.92
Franck, César	Pierné, Gabriel		.43	.16	.05	.76	.40	.15	.35	.57
Franck, César	d'Indy, Vincent	1872	.56	.25	.06	.82	.43	.12	.36	.54
Gade, Niels	Grieg, Edvard	1863	.36	.11	.03	.75	.39	.13	.55	.75
Gade, Niels	Heise, Peter		.30	.03	.00	.44	.07	.00	.52	.36
Gade, Niels	Jensen, Adolf		.36	.07	.01	.62	.11	.04	.31	.76
Gade, Niels	Kjerulf, Halfdan		.42	.06	.02	.59	.10	.03	.34	.69
Glazunov, Alexander	Prokofiev, Sergei		.46	.26	.12	.85	.58	.33	.68	.90
Glazunov, Alexander	Shostakovich, Dmitri		.48	.23	.10	.66	.35	.20	.36	.44
Glière, Reinhold	Khachaturian, Aram	1925	.27	.03	.00	.52	.07	.00	.00	.73
Glière, Reinhold	Miaskovsky, Nicolas		.33	.03	.00	.56	.07	.00	.37	.36
Glière, Reinhold	Prokofiev, Sergei	1902	.21	.04	.01	.59	.14	.03	.04	.38
Godard, Benjamin	Chaminade, Cécile		.39	.15	.05	.62	.21	.09	.14	.77
Goldmark, Karl	Sibelius, Jean	1890	.35	.14	.05	.80	.42	.16	.55	.83
Gounod, Charles-François	Bizet, Georges		.59	.40	.20	.90	.69	.40	.80	.81
Gounod, Charles-François	Debussy, Claude		.57	.38	.14	.81	.57	.25	.60	.77
Gounod, Charles-François	Franck, César		.58	.33	.12	.80	.51	.20	.52	.95
Gounod, Charles-François	Hahn, Reynaldo	1885	.55	.34	.15	.85	.65	.33	.63	.92
Gounod, Charles-François	Hüe, Georges		.35	.13	.03	.68	.38	.16	.46	.74
Gounod, Charles-François	Saint-Saëns, Camille		.64	.43	.19	.84	.60	.33	.79	.83
Halévy, Fromental	Bizet, Georges	1853	.28	.08	.00	.68	.20	.02	.25	.80
Halévy, Fromental	Gounod, Charles-François		.38	.11	.03	.66	.26	.06	.27	.76
Halévy, Fromental	Maillart, Louis		.37	.11	.00	.65	.28	.00	.19	.96
Halévy, Fromental	Masse, Victor		.34	.05	.00	.63	.13	.00	.36	.55
Halévy, Fromental	Offenbach, Jacques		.32	.07	.01	.60	.13	.02	.13	.64
Halévy, Fromental	Paladilhe, Émile		.38	.06	.00	.63	.11	.00	.46	.72
Halévy, Fromental	Saint-Saëns, Camille	1851	.27	.07	.02	.71	.30	.06	.47	.58
Halévy, Fromental	Weckerlin, Jean-Baptiste		.34	.09	.04	.59	.22	.08	.06	.60
Harris, Roy	Schuman, William		.29	.10	.00	.57	.17	.00	.71	.56
Haydn, Franz Joseph	Beethoven, Ludwig van		.69	.55	.36	.98	.92	.80	.91	.97
Hérold, Louis	Adam, Adolphe		.55	.27	.09	.88	.58	.21	.63	.75
Humperdinck, Engelbert	Griffes, Charles Tomlinson		.45	.25	.07	.80	.45	.23	.26	.56

TABLE F1 (*Continued*)

			Percent Shared			Cosine Similarity				
Teacher	Student	Year Met	2-Grams	3-Grams	4-Grams	2-Grams	3-Grams	4-Grams	Key	Time
Humperdinck, Engelbert	Scott, Cyril	1892	.33	.13	.02	.63	.22	.06	.28	.03
Humperdinck, Engelbert	Weill, Kurt		.26	.08	.01	.51	.14	.02	.21	.19
Ippolitov-Ivanov, Mikhail	Glière, Reinhold		.31	.04	.00	.61	.13	.00	.27	.91
Ireland, John	Britten, Benjamin	1930	.51	.29	.15	.84	.62	.36	.68	.79
Juon, Paul	Jacobi, Frederick		.23	.05	.02	.42	.10	.03	.00	.21
Juon, Paul	Kilpinen, Yrjö		.27	.08	.02	.43	.15	.04	.22	.46
Kodály, Zoltán	Bartók, Béla	1905	.50	.29	.12	.80	.61	.30	.81	.97
Liadoff, Anatoly	Miaskovsky, Nicolas		.49	.09	.02	.55	.16	.04	.39	.70
Liadoff, Anatoly	Prokofiev, Sergei		.34	.10	.02	.69	.29	.05	.63	.68
Liszt, Franz	Cornelius, C. Peter	1852	.35	.10	.01	.62	.39	.13	.24	.75
Liszt, Franz	Franck, César		.66	.32	.11	.83	.58	.21	.65	.91
Liszt, Franz	Hubay, Jeno		.19	.05	.02	.61	.22	.08	.56	.76
Liszt, Franz	Smetana, Bedřich	1848	.57	.35	.17	.91	.77	.49	.47	.83
Liszt, Franz	d'Albert, Eugen	1881	.16	.06	.03	.58	.45	.22	.35	.49
Liszt, Franz	d'Indy, Vincent	1873	.52	.22	.06	.87	.57	.22	.36	.68
Mascagni, Pietro	Zandonai, Riccardo		.33	.07	.04	.63	.33	.14	.00	.23
Massenet, Jules	Bemberg, Henri		.29	.09	.02	.78	.37	.13	.10	.66
Massenet, Jules	Charpentier, Gustave		.43	.14	.05	.70	.45	.21	.65	.85
Massenet, Jules	Chausson, Ernest	1879	.60	.24	.06	.77	.45	.22	.75	.42
Massenet, Jules	Enescu, George	1895	.57	.27	.10	.75	.49	.24	.35	.72
Massenet, Jules	Hahn, Reynaldo	1885	.55	.33	.11	.76	.56	.38	.55	.92
Massenet, Jules	Kreisler, Fritz		.51	.28	.10	.80	.50	.22	.72	.60
Massenet, Jules	Pierné, Gabriel		.49	.19	.05	.81	.50	.24	.54	.56
Massenet, Jules	Schmitt, Florent	1889	.32	.13	.04	.59	.36	.17	.17	.36
Messager, André	Beydts, Louis		.31	.00	.00	.37	.00	.00	.58	.85
Miaskovsky, Nicolas	Kabalevsky, Dmitry		.40	.06	.01	.51	.05	.01	.00	.15
Miaskovsky, Nicolas	Khachaturian, Aram	1929	.52	.15	.04	.67	.28	.05	.57	.45
Moniuszko, Stanisław	Cui, César	1856	.26	.09	.05	.41	.24	.13	.00	.00
Monteverde, Claudio	Schutz, Heinrich	1628	.53	.16	.04	.68	.37	.21	.79	.99

Moszkowski, Moritz	Nin, Joaquín		.52	.21	.06	.83	.65	.50	.33	.80
Moszkowski, Moritz	Schelling, Ernest	1882	.29	.07	.02	.32	.09	.03	.00	.48
Moszkowski, Moritz	Turina, Joaquín		.52	.18	.04	.79	.47	.19	.51	.78
Nin, Joaquín	Lecuona, Ernesto		.30	.12	.03	.54	.27	.05	.43	.87
Paderewski, Ignacy Jan	Schelling, Ernest		.21	.04	.03	.33	.13	.08	.00	.82
Parry, Hubert	Butterworth, George		.38	.15	.08	.63	.26	.15	.18	.25
Parry, Hubert	Holst, Gustav	1893	.39	.16	.02	.61	.32	.05	.15	.61
Parry, Hubert	Ireland, John		.35	.18	.05	.73	.45	.12	.72	.64
Parry, Hubert	Williams, Ralph Vaughan	1890	.36	.14	.03	.62	.39	.08	.64	.57
Piston, Walter	Bernstein, Leonard	1935	.36	.10	.02	.59	.25	.06	.59	.59
Ponchielli, Amilcare	Mascagni, Pietro	1883	.62	.24	.07	.81	.48	.21	.32	.88
Ponchielli, Amilcare	Puccini, Giacomo		.62	.26	.04	.79	.52	.23	.45	.83
Ravel, Maurice	Williams, Ralph Vaughan	1908	.55	.34	.12	.90	.76	.53	.83	.91
Reger, Max	Weinberger, Jaromir		.36	.12	.02	.77	.31	.04	.33	.86
Respighi, Ottorino	Hanson, Howard	1921	.41	.23	.09	.85	.57	.36	.34	.26
Rimsky-Korsakov, Nikolai	Arensky, Anton	1879	.43	.12	.04	.66	.28	.10	.73	.40
Rimsky-Korsakov, Nikolai	Glazunov, Alexander	1879	.52	.28	.09	.80	.51	.19	.69	.82
Rimsky-Korsakov, Nikolai	Gretchaninov, Alexander	1890	.29	.09	.02	.57	.22	.04	.45	.73
Rimsky-Korsakov, Nikolai	Ippolitov-Ivanov, Mikhail		.48	.23	.10	.79	.48	.23	.35	.70
Rimsky-Korsakov, Nikolai	Liadoff, Anatoly	1876	.42	.15	.05	.68	.30	.11	.76	.78
Rimsky-Korsakov, Nikolai	Miaskovsky, Nicolas		.40	.12	.02	.62	.23	.04	.26	.70
Rimsky-Korsakov, Nikolai	Prokofiev, Sergei	1904	.56	.29	.13	.84	.65	.32	.61	.76
Rimsky-Korsakov, Nikolai	Rachmaninov, Sergei		.54	.31	.11	.88	.61	.28	.68	.31
Rimsky-Korsakov, Nikolai	Respighi, Ottorino	1900	.61	.35	.17	.88	.69	.40	.76	.91
Rimsky-Korsakov, Nikolai	Stravinsky, Igor	1902	.57	.31	.13	.81	.59	.29	.70	.90
Roussel, Albert	Auric, Georges	1914	.33	.11	.04	.43	.19	.05	.20	.42
Roussel, Albert	Satie, Erik		.38	.09	.02	.44	.13	.03	.63	.70
Rubinstein, Anton	Tchaikovsky, Piotr Ilich		.59	.30	.12	.87	.58	.32	.62	.83
Saint-Saëns, Camille	Fauré, Gabriel	1861	.65	.40	.18	.94	.68	.37	.74	.89
Saint-Saëns, Camille	Hahn, Reynaldo	1885	.43	.28	.12	.83	.69	.52	.71	.95
Saint-Saëns, Camille	Messager, André		.17	.05	.01	.50	.18	.04	.33	.50
Satie, Erik	Poulenc, Francis	1914	.38	.13	.02	.47	.18	.03	.52	.41
Scarlatti, Alessandro	Scarlatti, Domenico	1685	.49	.20	.08	.86	.60	.31	.56	.70

TABLE F1 (*Continued*)

Teacher	Student	Year Met	Percent Shared			Cosine Similarity				
			2-Grams	3-Grams	4-Grams	2-Grams	3-Grams	4-Grams	Key	Time
Schmitt, Florent	Auric, Georges	1913	.49	.21	.04	.64	.29	.09	.12	.23
Schoenberg, Arnold	Berg, Alban		.15	.02	.00	.28	.05	.00	.22	.61
Spohr, Louis	Hartmann, Johann Peter		.45	.14	.08	.61	.28	.15	.21	.95
Stanford, Charles	Butterworth, George		.38	.09	.00	.47	.12	.00	.38	.74
Stanford, Charles	Coleridge-Taylor, Samuel		.40	.14	.02	.52	.22	.03	.38	.28
Stanford, Charles	Holst, Gustav	1893	.39	.14	.05	.79	.35	.10	.34	.44
Stanford, Charles	Ireland, John		.35	.14	.06	.74	.39	.17	.39	.29
Stanford, Charles	Williams, Ralph Vaughan	1890	.36	.13	.04	.65	.32	.13	.41	.61
Strauss, Richard	Jongen, Joseph		.18	.04	.01	.45	.12	.05	.53	.67
Sullivan, Arthur	d'Albert, Eugen		.22	.09	.03	.74	.62	.56	.40	.52
Suppé, Franz von	De Koven, Reginald		.31	.13	.04	.81	.60	.38	.49	.61
Suppé, Franz von	Millocker, Carl		.48	.22	.05	.73	.37	.10	.60	.50
Tartini, Giuseppe	Nardini, Pietro	1734	.36	.12	.02	.49	.23	.07	.68	.70
Telemann, Georg Philipp	Bach, Wilhelm		.53	.19	.04	.84	.33	.05	.05	.83
Thomas, Ambroise	Enescu, George	1895	.58	.26	.07	.77	.43	.11	.51	.78
Thomas, Ambroise	Inghelbrecht, Désiré-Émile	1887	.40	.15	.05	.74	.40	.08	.54	.92
Thomas, Ambroise	Massenet, Jules	1861	.72	.36	.09	.73	.38	.13	.60	.57
Thomson, Virgil	Bernstein, Leonard	1932	.52	.16	.03	.64	.23	.06	.17	.59
Vieuxtemps, Henri	Godard, Benjamin		.37	.17	.04	.65	.29	.06	.63	.53
Vieuxtemps, Henri	Hubay, Jenő	1878	.40	.09	.03	.55	.14	.07	.22	.05
Vinci, Leonardo	Pergolesi, Giovanni		.36	.16	.08	.71	.43	.23	.27	.65
Vivaldi, Antonio	Bach, Johann Sebastian		.54	.29	.13	.86	.65	.46	.71	.96
Wagner, Richard	Humperdinck, Engelbert	1880	.36	.24	.10	.91	.61	.31	.68	.70
Weber, Carl von	Benedict, Julius	1821	.23	.07	.02	.57	.35	.17	.24	.41
Weyse, Christoph E.F.	Hartmann, Johann Peter		.53	.15	.04	.59	.24	.09	.29	.62
Widor, Charles-Marie	Honegger, Arthur	1911	.15	.04	.01	.58	.41	.16	.19	.34
Widor, Charles-Marie	Milhaud, Darius		.27	.08	.02	.58	.50	.38	.03	.36
Williams, Ralph Vaughan	Britten, Benjamin	1930	.63	.30	.13	.88	.73	.47	.70	.71
Williams, Ralph Vaughan	Gibbs, Cecil Armstrong		.23	.07	.03	.66	.32	.12	.61	.76

References

Abril, Carlos R., and Brent M. Gault. 2016. *Teaching General Music: Approaches, Issues, and Viewpoints.* New York: Oxford Univ. Press.

Aghion, Philippe, Mathias Dewatripont, and Jeremy C. Stein. 2008. "Academic Freedom, Private-Sector Focus, and the Process of Innovation." *RAND J. Econ.* 39 (3): 617–35.

Akcigit, Ufuk, Santiago Caicedo, Ernest Miguelez, Stefanie Stantcheva, and Valerio Sterzi. 2018. "Dancing with the Stars: Innovation through Interactions." Working Paper no. 24466 (March), NBER, Cambridge, MA.

Azoulay, Pierre, Toby E. Stuart, and Christopher C. Liu. 2017. "Social Influence Given (Partially) Deliberate Matching: Career Imprints in the Creation of Academic Entrepreneurs." *American J. Sociology* 122 (4): 1223–71.

Barlow, Harold, and Sam Morgenstern. 1975. *A Dictionary of Musical Themes.* New York: Crown.

———. 1976. *A Dictionary of Opera and Song Themes.* New York: Crown.

Baumol, William J., and Hilda Baumol. 1994. "On The Economics of Musical Composition in Mozart's Vienna." *J. Cultural Econ.* 18 (3): 171–98.

Bertrand, Marianne, and Antoinette Schoar. 2003. "Managing with Style: The Effect of Managers on Firm Policies." *Q.J.E.* 118 (4): 1169–208.

Bisin, Alberto, and Thierry Verdier. 2001. "The Economics of Cultural Transmission and the Dynamics of Preferences." *J. Econ. Theory* 97 (2): 298–319.

———. 2011. "The Economics of Cultural Transmission and Socialization." In *Handbook of Social Economics,* vol. 1, edited by Jess Benhabib, Alberto Bisin, and Matthew O. Jackson, 339–416. Amsterdam: North-Holland.

Bonds, Mark E. 2006. *Music as Thought: Listening to the Symphony in the Age of Beethoven.* Princeton, NJ: Princeton Univ. Press.

Bordo, Michael D., and Klodiana Istrefi. 2018. "Perceived FOMC: The Making of Hawks, Doves and Swingers." Working Paper no. 24650 (May), NBER, Cambridge, MA.

Borowiecki, Karol J. 2013. "Geographic Clustering and Productivity: An Instrumental Variable Approach for Classical Composers." *J. Urban Econ.* 73 (1): 94–110.

———. 2015a. "Agglomeration Economies in Classical Music." *Papers Regional Sci.* 94 (3): 443–68.

———. 2015b. "Historical Origins of Cultural Supply in Italy." *Oxford Econ. Papers* 67 (3): 781–805.

———. 2017. "How Are You, My Dearest Mozart? Well-Being and Creativity of Three Famous Composers Based on Their Letters." *Rev. Econ. and Statis.* 99 (4): 591–605.

Borowiecki, Karol J., and Caterina Mauri. 2021. "Originality, Influence, and Success: A Model of Creative Style." Discussion Papers on Bus. and Econ. no. 6/2021, University of Southern Denmark, Odense.

Burkholder, J. Peter. 2001. "Borrowing." In *Grove Music Online.* https://doi.org/10.1093/gmo/9781561592630.article.52918.

Chan, Tian H., Jürgen Mihm, and Manuel E. Sosa. 2018. "On Styles in Product Design: An Analysis of US Design Patents." *Management Sci.* 64 (3): 1230–49.

Chetty, Raj, John N. Friedman, and Jonah E. Rockoff. 2014a. "Measuring the Impacts of Teachers I: Evaluating Bias in Teacher Value-Added Estimates." *A.E.R.* 104 (9): 2593–632.

———. 2014b. "Measuring the Impacts of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood." *A.E.R.* 104 (9): 2633–79.

Costanza, Peter, and Timothy Russell. 2017. "Methodologies in Music Education." In *Critical Essays in Music Education*, vol. 1, edited by Marvelene C. Moore, 255–67. London: Routledge.

da Fonseca-Wollheim, Corinna. 2017. "Immortal Fingertips: Music Teachers Live On through Their Students." *New York Times*, May 12. https://www.nytimes.com/2017/05/12/arts/music/immortal-fingertips-music-teachers-live-on-through-their-students.html.

de la Croix, David, Matthias Doepke, and Joel Mokyr. 2018. "Clans, Guilds, and Markets: Apprenticeship, Institutions and Growth in the Preindustrial Economy." *Q.J.E.* 133 (1): 1–70.

Feinstein, Jonathan S. 2006. *The Nature of Creative Development.* Stanford, CA: Stanford Bus.

———. 2011. "Optimal Learning Patterns for Creativity Generation in a Field." *A.E.R.* 101 (3): 227–32.

Fernie, Eric. 1995. *Art History and Its Methods: A Critical Anthology*. London: Phaidon.

Forte, Allen. 1979. *Tonal Harmony in Concept and Practice.* New York: Holt, Rinehart & Winston.

Foster, Peter, Matthias Mauch, and Simon Dixon. 2014. "Sequential Complexity as a Descriptor for Musical Similarity." *IEEE/ACM Transactions on Audio, Speech and Language Processing (TASLP)* 22 (12): 1965–77.

Gergaud, Olivier, Morgane Laouenan, and Etienne Wasmer. 2016. "A Brief History of Human Time: Exploring a Database of 'Notable People.'" Discussion Paper no. 2016-03, Sciences Po Dept. Econ.

Grove Music Online. 2016–21. Oxford Music Online: *Grove Music Online.* http://www.oxfordmusiconline.com.

Hellmanzik, Christiane. 2010. "Location Matters: Estimating Cluster Premiums for Prominent Modern Artists." *European Econ. Rev.* 54 (2): 199–218.

Howes, Anton. 2017. "The Spread of Improvement: Why Innovation Accelerated in Britain 1547–1851." Manuscript, Brown Univ.

IMSLP (International Music Score Library Project). 2016–19. IMSLP/Petrucci Music Library. https://imslp.org.

Jackson, C. Kirabo, Jonah E. Rockoff, and Douglas O. Staiger. 2014. "Teacher Effects and Teacher-Related Policies." *Ann. Rev. Econ.* 6:801–25.

Jones, Charles I. 2005. "Growth and Ideas." In *Handbook of Economic Growth*, vol. 1B, edited by Philippe Aghion and Steven N. Durlauf, 1063–111. Amsterdam: North-Holland.

Laborde, Jean-Benjamin de. 1780. *Essai sur la musique ancienne et moderne.* Paris: Ph. D. Pierres & Eugène Onfroy.

Livingston, Ernest F. 1971. "The Place of Music in German Education around 1600." *J. Res. Music Educ.* 19 (2): 144–67.

Lucas, Robert E., Jr. 2008. "Ideas and Growth." Working Paper no. 14133 (June), NBER, Cambridge, MA.

Margo, Robert A. 2018. "The Integration of Economic History into Economics." *Cliometrica* 12 (3): 377–406.

Mark, Michael. 2008. *A Concise History of American Music Education.* Lanham, MD: Rowman & Littlefield Educ.

Mauch, Matthias, Robert M. MacCallum, Mark Levy, and Armand M. Leroi. 2015. "The Evolution of Popular Music: USA 1960–2010." *Royal Soc. Open Sci.* 2 (5): 150081. https://doi.org/10.1098/rsos.150081.

Meisenzahl, Ralf R., and Joel Mokyr. 2011. "The Rate and Direction of Invention in the British Industrial Revolution: Incentives and Institutions." In *The Rate*

and Direction of Inventive Activity Revisited, edited by Josh Lerner and Scott Stern, 443–79. Chicago: Univ. Chicago Press (for NBER).
Mokyr, Joel. 2009. "Intellectual Property Rights, the Industrial Revolution, and the Beginnings of Modern Economic Growth." *A.E.R.* 99 (2): 349–55.
———. 2016. *A Culture of Growth: The Origins of the Modern Economy*. Princeton, NJ: Princeton Univ. Press.
Murray, Charles. 2003. *Human Accomplishment: The Pursuit of Excellence in the Arts and Sciences, 800 B.C. to 1950*. New York: Harper Collins.
O'Hagan, John, and Karol J. Borowiecki. 2010. "Birth Location, Migration, and Clustering of Important Composers." *Hist. Methods* 43 (2): 81–90.
Pfitzinger, Scott. 2017. *Composer Genealogies: A Compendium of Composers, Their Teachers, and Their Students*. Lanham, MD: Rowman & Littlefield.
Rivkin, Steven G., Eric A. Hanushek, and John F. Kain. 2005. "Teachers, Schools, and Academic Achievement." *Econometrica* 73 (2): 417–58.
Rockoff, Jonah E. 2004. "The Impact of Individual Teachers on Student Achievement: Evidence from Panel Data." *A.E.R.* May 94 (2): 247–52.
Scherer, Frederic M. 2004. *Quarter Notes and Bank Notes: The Economics of Music Composition in the Eighteenth and Nineteenth Centuries*. Princeton, NJ: Princeton Univ. Press.
Serrà, Joan, Álvaro Corral, Marián Boguñá, Martin Haro, and Josep L. Arcos. 2012. "Measuring the Evolution of Contemporary Western Popular Music." *Scientific Reports* 2:521. https://doi.org/10.1038/srep00521.
Simonton, Dean Keith. 1980. "Thematic Fame and Melodic Originality in Classical Music: A Multivariate Computer-Content Analysis." *J. Personality* 48 (2): 206–19.
———. 1983. "Intergenerational Transfer of Individual Differences in Hereditary Monarchs: Genetic, Role-Modeling, Cohort, or Sociocultural Effects?" *J. Personality and Soc. Psychology* 44 (2): 354–64.
———. 1984a. "Artistic Creativity and Interpersonal Relationships across and within Generations." *J. Personality and Soc. Psychology* 46 (6): 1273–86.
———. 1984b. "Melodic Structure and Note Transition Probabilities: A Content Analysis of 15,618 Classical Themes." *Psychology Music* 12 (1): 3–16.
———. 2004. *Creativity in Science: Chance, Logic, Genius, and Zeitgeist*. Cambridge: Cambridge Univ. Press.
———. 2014. "The Mad-Genius Paradox: Can Creative People Be More Mentally Healthy but Highly Creative People More Mentally Ill?" *Perspectives Psychological Sci.* 9 (5): 470–80.
Smith, Charles H., and Patrick Georges. 2014. "Composer Similarities through the Classical Music Navigator: Similarity Inference from Composer Influences." *Empirical Studies Arts* 32 (2): 205–29.
Squicciarini, Mara P., and Nico Voigtländer. 2015. "Human Capital and Industrialization: Evidence from the Age of Enlightenment." *Q.J.E.* 130 (4): 1825–83.
Tol, Richard S. J. 2018. "Rise of the Kniesians: The Professor-Student Network of Nobel Laureates in Economics." Working paper, Dept. Econ., Univ. Sussex.
Viig, Tine G. 2015. "Composition in Music Education: A Literature Review of 10 Years of Research Articles Published in Music Education Journals." In *Nordic Research in Music Education Yearbook*, vol. 16, edited by Øivind Varkøy, Eva Georgii-Hemming, Sven-Erik Holgersen, and Lauri Väkevä, 227–57. Oslo: Norwegian Acad. Music.
Waldinger, Fabian. 2010. "Quality Matters: The Expulsion of Professors and the Consequences for PhD Student Outcomes in Nazi Germany." *J.P.E.* 118 (4): 787–831.

Weiss, Christof, Matthias Mauch, and Simon Dixon. 2014. "Timbre-Invariant Audio Features for Style Analysis of Classical Music." In *Music Technology Meets Philosophy: From Digital Echos to Virtual Echos. Proceedings of the ICMC | SMC | 2014: 40th International Computer Music Conference Joint with the 11th Sound and Music Computing Conference*, vol. 2, edited by Anastasia Georgaki and Giorgios Kouroupetroglou, 1461–68. San Francisco: Internat. Computer Music Assoc.