

Networks in philosophy: Social networks and employment in academic philosophy

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Abstract

In recent years, the “science of science” has combined computational methods with novel data sources to understand the dynamics of research communities. Many of the questions investigated by science of science are also relevant to academic philosophy. To what extent can the discipline be divided into subfields with different methods and topics? How are prestige and credit distributed across the discipline? And how do these factors interact with other factors, such as gender, to shape job market outcomes? Using job market data for anglophone academic philosophy, this paper finds, first, evidence that is consistent with the analytic-continental divide but is also consistent with other, more complex ways of organizing academic philosophy into distinct intellectual traditions; second, a clear prestige hierarchy, dividing Ph.D. programs into two distinct prestige categories; and, third, evidence that gender, prestige, and country have notable effects on academic job market outcomes for recent philosophy Ph.Ds.

KEYWORDS

academic job market, analytic-continental divide, gender bias, network analysis, prestige bias, research communities

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1 | INTRODUCTION AND BACKGROUND

In recent years, the interdisciplinary field of “science of science” has combined computational methods with novel data sources in order to understand the dynamics of research communities (Fortunato et al. 2018). As the name suggests, science of science is primarily focused on science and technology, with less attention to the humanities. However, many of the questions investigated by science of science are also relevant to academic philosophy. To what extent can the discipline be divided into subfields with different methods and topics (Alcoff 2013; West et al. 2013)? How are prestige and credit distributed across the discipline (De Cruz 2018; Morgan et al. 2018)? And how do they interact with other factors, such as gender, to shape job market outcomes (Burriss 2004; Weinberg 2016)?

In this paper, we provide some empirically informed answers to these questions by applying computational methods to data on Ph.D. graduates in philosophy from primarily English-language programs around the world. Our findings provide an understanding of how academic philosophy is structured in the anglophone world.

Excluding this introduction and the summary, the paper is organized into four sections, starting with one brief section on background (2), followed by three major sections on the primary questions of the paper (mentioned above).

Section 3 uses cluster analysis to examine the way philosophy programs group together. While this analysis does support the existence of the much discussed “analytic-continental” divide, there is better support for a three-way division, according to which philosophy of science is distinct from both the analytic and the continental traditions. We also show that a more fine-grained analysis can pick out notable subdivisions, such as the division between “core” analytic philosophy and applied ethics.

Section 4 conducts a network analysis of hiring data—tracing who hires whom—to examine prestige in academic philosophy. Using two different approaches, we find a clear division of philosophy programs into “high-prestige” and “low-prestige” groups.

Section 5 uses regression modeling to examine how both individual-level and program-level factors make a difference in job market outcomes for recent Ph.D.s. We find evidence of notable effects for individual gender, program prestige, and the country in which the Ph.D. program is located. Each section provides a detailed but accessible discussion of our methods. Section 6 provides a brief conclusion.

To some extent, these findings support common perceptions that academic philosophers have about the discipline, such as the dominance of a few high-prestige analytic programs. In other respects these findings challenge prevailing wisdom. For example, many “high-prestige” Ph.D. programs have low permanent placement rates, while many “low-prestige” programs have high permanent placement rates. In other words, graduating from a prestigious program is far from a guarantee that an individual will be successful on the academic job market.

2 | THE ACADEMIC PHILOSOPHY DATA AND ANALYSIS PROJECT

The paper uses data obtained from the Academic Philosophy Data and Analysis (APDA) database of recent philosophy Ph.D.s. This section provides background on APDA and relevant aspects of its sampling frame, data collection, and data cleaning. Two distinct datasets were generated for the clustering and network-analysis parts of the current project, respectively, so some details of the data used vary between analyses. Details on each of these datasets are given in the respective methods sections below.

APDA is a multiyear, collaborative project that aims to track information related to job market placement for recent Ph.D. graduates in philosophy. Since 2011, information has been

collected from public sources, such as program placement websites, as well as private sources, such as the graduates themselves.¹ Thanks in part to funding from the American Philosophical Association, the database has grown substantially in recent years, from around 700 individuals in 2014 to more than 14,300 at the end of 2021, including around 4,300 current Ph.D. students. Along with year-to-year data-gathering and accuracy checks, the project has run several surveys of past graduates, including current students in the two most recent surveys (Jennings and Dayer 2022; Jennings et al. 2019). Many survey participants updated the information described above while taking part in the yearly survey. During the 2021 data checks, 129 of 199 philosophy Ph.D. programs were found to have either a placement page or public dissertation records that could be used to verify APDA's data, and these are the programs included in the analyses for this paper.

The APDA project has made several data-collection and coding decisions that are relevant to the current project. First, the project aims to cover all recent Ph.D. graduates from all departments that offer a primarily English-language doctoral program in philosophy. APDA is a near-complete record of philosophy Ph.D. graduates in the United States, including 90 percent of the total number of graduates tracked by the Survey of Earned Doctorates for the years covered in this paper (2012–2019).² Yet, it is unclear how complete its data are outside the United States; only 27 of the 129 programs covered in this paper are outside the United States (14 in the United Kingdom, 9 in Canada, 2 in New Zealand, 1 in Australia, and 1 in the Netherlands). Second, APDA gathers information on gender, rather than sex. Gender is attributed based either on first names (using an automated web service, <https://genderize.io/>, that uses binary gender) or on self-reporting (including “nonbinary” and “other” options that replace automated attributions). Third, race and ethnicity are based only on self-reporting through the survey; because this makes race and ethnicity data patchy, these variables were not used in the current project. Fourth, APDA segments primary area of specialization into four main categories, roughly following the taxonomy used by PhilPapers (<https://philpapers.org/>): LEMM (language, epistemology, mind, and metaphysics); value theory; history and traditions; and science, logic, and math. Within those categories are forty-one areas of specialization, provided in Figure 1.

APDA classifies job market placements into three main types: permanent academic, temporary academic, and nonacademic. Permanent academic placements include tenure-track positions, permanent lectureships, permanent instructor positions, permanent adjunct positions, and other permanent positions. Temporary academic placements include fellowships and postdoctoral positions, visiting positions, temporary lectureships, temporary instructor positions, temporary adjunct positions, and other temporary positions. In some cases it is difficult to determine whether a position is permanent or temporary, but in most cases this is noted by either the job candidate or the program placement page. The network and regression analyses below are based on each individual's most recent placement as of summer 2021.³

APDA's survey methodology varies somewhat from year to year but has standardly involved an invitation to all those in the database for whom we have contact information (the project currently has email addresses for 10,323 of the 14,390 people in the database and has had 2,293 of these individuals participate in the survey). In the first year, participants were included in a drawing for Amazon gift cards (one \$50 card was distributed to one random participant of every fifty participants). In subsequent years, participation was strictly voluntary. In each

¹Collected information includes: name; email address; gender; race/ethnicity; primary area of specialization; graduating university, program, and year; university, placement type, and year for academic placements; and, for nonacademic placements, company/institution, position, and year.

²The raw numbers can be seen in the figure here: <https://faculty.ucmerced.edu/cjennings3/phildata/SEDnew.png>.

³The data were pulled in August 2021, but the data checks occurred in June through August.

<p><i>LEMM</i>: Action, Epistemology, Language, Metaphilosophy (including Experimental Philosophy), Metaphysics, Mind, and Religion</p> <p><i>Value Theory</i>: Aesthetics, Applied Ethics (including Bio and Medical), Education, Ethics, Gender/Race /Sexuality/Disability Studies, Law, Metaethics, Social/Political, and Value (General)</p> <p><i>History and Traditions</i>: 19th/20th, African, American (including Latin American), Analytic (History of), Ancient, Asian, Comparative, Continental (including Phenomenology), German (including Kant), History (General), Medieval /Renaissance, and Modern</p> <p><i>Science, Logic, and Math</i>: Biology (including Environmental), Cognitive Science/Psychology /Neuroscience/Linguistics, Decision Theory, Economics, Logic, Math, Physics, Science (General), and Technology</p>

FIGURE 1 Areas of specialization (AOS) under each AOS category

survey, participants are asked about “keywords” that “describe theoretical perspectives, methodologies, and/or training that especially distinguish your graduate program.” The keyword options roughly align with the areas of specialization listed in Figure 1, but they were developed independently, using text-based entries from the first APDA survey.⁴ In total, 2,146 participants provided keyword information as of August 2021. The provided areas of specialization and keywords are the basis for the cluster analysis below.

While APDA data give us a nearly comprehensive view of the recent academic job market in philosophy, a few limitations are worth noting. Most obviously, the APDA project has only existed since 2011 and has the most reliable coverage for graduates between 2012 and 2019. This means that we cannot speak to long-term trends, such as placement ten or more years after graduation. Further, in recent years APDA has begun collecting information on multiple demographic factors (such as race and ethnicity, sexual orientation, trans identity, disability, class background, and nationality), but this information is provided as self-reporting through the survey and so is limited to a subset of the database. Thus, while these demographic factors may well impact our analyses at both the individual and the program levels, we are unable to include them. Finally, APDA is focused on anglophone programs; the data are thus not reliable for those regions where English is not the language spoken by the majority.

For privacy reasons we cannot make the data publicly available. We can, however, make the data available to researchers who have received IRB (Institutional Review Board) approval or exempt status. All analysis was conducted in R version 4.1.0 (R Core Team 2021). All code used in this study is available at <https://github.com/dhicks/apda-network>. Besides the packages acknowledged below in the specific methods sections, our analysis made significant use of the tidyverse suite of packages (Wickham and RStudio 2017).

⁴In addition to the areas of specialization listed above, they include contemporary, critical theory, French, interdisciplinary, Islamic, naturalist/empirical, non-Western, pluralist, and pragmatism. They do not include 19th/20th, action, comparative, decision theory, economics, education, metaethics, or technology.

3 | SPECIALIZATION CLUSTERING AND THE ANALYTIC-CONTINENTAL DIVIDE

Perhaps one of the most discussed sociological and intellectual divisions in academic philosophy is the so-called analytic-continental divide. It has been discussed in popular venues like the *New York Times* as well as in edited volumes on the topic (Bell, Cutrofello, and Livingston 2015; Gutting 2012). We will not rehearse here the history of this divide or the details of the split, but it is worth providing a few words of characterization for those outside the discipline or those otherwise unaware of the divide (Friedman 2000). Briefly, analytic philosophy developed primarily in anglophone programs with a methodology that emphasizes formal logic and conceptual analysis. As Gutting (2021) puts it, “The basic idea [of the analytic tradition] was that philosophical problems could be solved [or dissolved] by logically analyzing key terms, concepts or propositions.” This was later supplemented by a “naturalized program” (Quine 1969) that focuses on deriving insights about philosophical problems from the knowledge produced by scientific inquiry to a much greater degree than in previous time periods (Kim 2003). In contrast, continental philosophy primarily developed in mid-twentieth-century French and German academic philosophy before also being adopted by some anglophone scholars and programs. As Gutting (2012) puts it, “Continental philosophies of experience try to probe beneath the concepts of everyday experience to discover the meanings that underlie them, to think the conditions for the possibility of our concepts.... Continental philosophies of imagination try to think beyond those concepts, to, in some sense, think what is impossible.”

Despite this background, the strict division of academic philosophy into two main traditions has been put into question. Some authors have provided characterizations of analytic philosophy that emphasize more historical, stylistic, or topical traits, taking away the focus from unique shared methodologies or values such as “precision” and “rigor” (Glock 2008; Levy 2003). For its part, continental philosophy has come to be used as a moniker for such a wide variety of intellectual currents—phenomenology, (post)structuralism, Marxism, hermeneutics, existentialism, critical theory, and even the history of continental European philosophy—that it is increasingly difficult to treat it as a single tradition (Critchley 2001; Schrift 2010). Continental programs have also been especially hospitable to philosophers working in the American pragmatist and Catholic traditions. These various methods and traditions seem mainly to share the trait of just not being part of the analytic tradition (Conant 2015; Toadvine 2012; West 2010). Finally, certain thinkers, such as Kant and Wittgenstein, have been important to both sides of the “divide.”

In light of these criticisms, we wondered whether the analytic-continental divide could still usefully characterize academic philosophy, or if other divisions might be more informative. To explore this, we used the keywords provided in past APDA surveys as well as the areas of specialization provided for current students and recent graduates to see which keywords and areas tend to group together at the department level. We found that while there is a prominent split in the field that might be described as reflecting the analytic-continental divide, there is significant overlap between the two sides of this split. This might be, in part, because historical and pluralist programs tend to include both traditions. Further, splitting the field into *three* groups provides a better overall group structure according to at least one measure; on this picture, philosophy of science is distinguishable from both analytic and continental philosophy. An additional analysis finds evidence of even more fine-grained viable divisions, such as between “core” analytic philosophy and applied ethics, and between pluralism-pragmatism and “core” continental philosophy.

3.1 | Methods

In machine learning, *cluster analysis* is any method that arranges units of analysis into subsets—that is, clusters—based on some measure of similarity between the variables that characterize them (James et al. 2013, 10.3). In the current project, the units of analysis are philosophy Ph.D. programs, and the variables that characterize them are aggregated from (1) the areas of specialization (AOS) of their Ph.D. graduates and (2) the “keyword” survey responses. Recall that the survey respondents are asked to select keywords that distinguish their Ph.D. program. We hypothesized that if the analytic-continental divide exists at the departmental level, it will create patterns of association among these AOS and keyword variables and thus that the programs will cluster along this divide.

Data were pulled from the APDA database on 18 and 19 August 2021 for both sets of variables (AOS and keywords). For this cluster analysis, we used only programs with validated data as of summer 2021 that also had AOS and keyword data (127 out of 129 total programs), and only keywords selected in responses from at least 5 percent of these 127 programs (39 out of 41 keywords). To account for differences in program size, both AOS and keyword counts were normalized at the program level by dividing by the total number of graduates or respondents (respectively) from each program.

We used *agglomerative hierarchical cluster analysis*, which produces a tree or hierarchy of potential clustering solutions, ranging from one giant cluster at one extreme (all units in a single cluster) to singleton clusters at the other (all units in their own individual cluster).⁵ This method does not automatically select any particular number of clusters k . For each value of k from 2 to 10, we scored the quality of the k -cluster solution using the silhouette index (Arbelaitz et al. 2013; Rousseeuw 1987), which compares average within-cluster and between-cluster distances.

Finally, we developed interpretive labels for each cluster by examining the “traits” that distinguish that cluster from other clusters. To do this, we transformed each AOS or keyword value into a z-score. If a program has a large positive z-score for a variable (greater than, say, 2), this means that the program has a substantially higher than average value for that variable in comparison to other programs. We then averaged the z-scores for each AOS and keyword across the programs within each cluster. So if the cluster has a high z-score for AOS Ethics, this means that its programs tend to produce more Ph.D.s specializing in ethics than average.

3.2 | Results and discussion

By design, our hierarchical cluster analysis identifies a nested structure of topics or fields of study. At the coarsest level of analysis, we find evidence of the analytic-continental divide. Philosophy of science emerges as a distinct cluster, however, and the “continental” label appears to be an oversimplification.

The agglomerative coefficient of the hierarchical clustering using our chosen methods is 0.91, which is close to the maximum of 1. This value suggests that our hierarchical tree of clusters is well structured. Figure 2 shows the silhouette index for values of k (number of clusters) from 2 to 10; higher values suggest that points are better grouped than lower values. The silhouette values range from 0.12 at $k = 7$ to about 0.25 at $k = 3$. To interpret the clusters, we focus on $k = 2$ and $k = 3$ as the highest values of the silhouette and examine $k = 6$ to aid interpretation of the 2-cluster and 3-cluster solutions.

⁵Specifically, we first calculated Pearson correlation similarity in each pair of programs, across the AOS and keyword values, then used Ward’s method (Ward 1963) to agglomerate the cluster hierarchy.

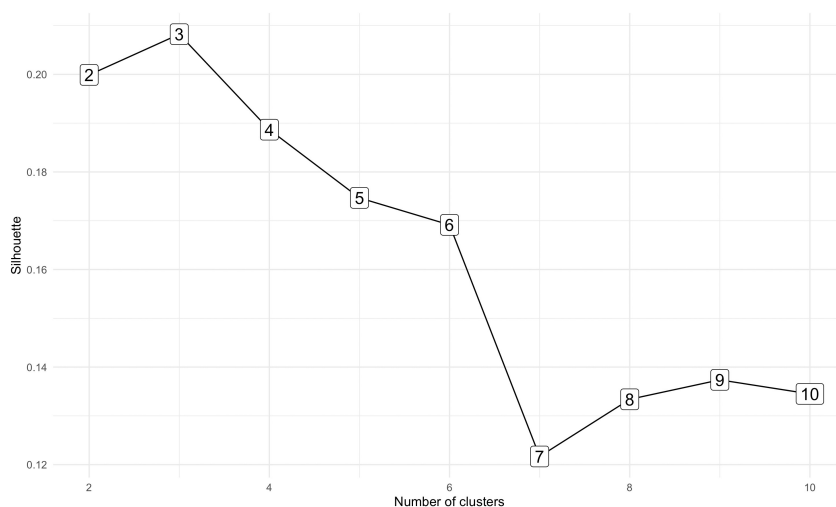


FIGURE 2 Silhouette index and silhouette widths for values of k (number of clusters) between $k = 2$ and $k = 10$. The silhouette index ranges between -1 and 1 ; higher values indicate that programs are clustered with relatively similar programs. The silhouette index is calculated in two steps. First, for each program, we calculate its silhouette width, the difference between its distance to the next-closest cluster and its distance to its own cluster. The silhouette index is the average across all programs.

Figure 3 shows the cut tree for values of $k = 2, 3, 6$. Note that the structure of the tree is the same in each panel; the only difference is how the branches are colored (or shaded in gray), indicating different numbers of clusters. Each different colored branch of the tree is a different cluster.

For $k = 2$ (Figure 3a), Cluster 1 includes 87 programs and Cluster 2 includes 40 programs. The positive traits for Cluster 1 are the keywords Analytic ($z = 0.29$), Naturalist/Empirical (0.26), AOS Mind (0.23), Mind (0.22), and Logic/Formal (0.21); its negative traits are Continental (-0.47), Phenomenology (-0.37), AOS Continental (0.36), Critical Theory (0.35), and German (-0.31). These traits are reversed for Cluster 2: the positive traits for Cluster 1 are the negative traits for Cluster 2, and vice versa. Based on these traits, this clustering appears to correspond to the analytic-continental divide. Examining the 6-cluster solution below, however, will indicate that the “continental” label, while familiar to many philosophers, is likely to be an oversimplification.

For $k = 3$ (Figure 3b), the “analytic” cluster separates into two sub-clusters. The first of these two now includes 72 programs, and the second includes 15 programs; the “continental” cluster is unchanged from $k = 2$ with 40 programs. The positive traits of the first cluster are now keywords Analytic (0.43), Mind (0.38), AOS Mind (0.35), Epistemology (0.28), and AOS Metaphysics (0.25). All of these fall under the LEMM AOS category. The positive traits for Cluster 3 are the same as the 2-cluster solution: Continental, Phenomenology, AOS Continental, Critical Theory, and German. For the new Cluster 2, the positive traits are Biology (2.18), AOS Science (1.88), AOS Biology (1.71), History and Philosophy of Science (1.44), and Naturalist/Empirical (1.42). This cluster appears to correspond to philosophy of science. When we use these clustering methods, philosophy of science is closer to analytic philosophy than to continental philosophy, but it is clearly distinguishable from analytic philosophy. This analytic philosophy/philosophy of science distinction is highlighted by the negative traits of this cluster, which include AOS Ethics (-0.65) and Mind (-0.57).

These three traditions within academic philosophy often have gendered associations. Because of their associations with logic and formal rigor, analytic philosophy and

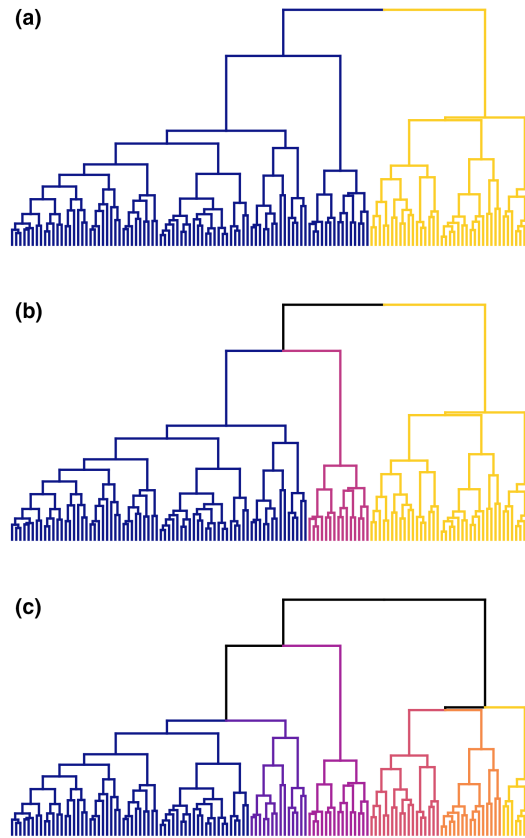


FIGURE 3 Dendrograms showing the different cluster assignments for $k = 2, 3, 6$ in *a, b,* and *c,* respectively. The structure is the same in each panel; only the branch colors are different, indicating different numbers of clusters. The cluster numbers used in the text correspond to the order of the clusters in each panel, from left to right.

philosophy of science are both often associated with masculinity, while continental philosophy's use of interpretive methods (such as phenomenology) is often associated with femininity. For example, several feminist philosophers have criticized the analytic tradition by arguing that it relies on masculine assumptions and has difficulty accommodating key feminist insights, such as the idea that knowledge is socially situated. Other feminist philosophers, however, have argued that the analytic tradition has important conceptual tools for feminist philosophy (Garry 2018). Gender schema theory proposes that people tend to choose careers whose gender associations match their own gender identity; for example, according to this theory, men will tend to choose careers with masculine associations, such as science and technology, while women will tend to choose careers with feminine associations, such as nursing and elementary education (Calhoun 2009; Haslanger 2008). If analytic philosophy and philosophy of science do have masculine associations, while continental philosophy has feminine associations, we might expect that programs in the continental cluster would have a higher share of women graduates compared to programs in the analytic and philosophy of science clusters.⁶ Figure 4 suggests that this is not the case, however. The figure shows each program in each of the three clusters, with a bar indicating the

⁶We thank an anonymous referee for suggesting this analysis.

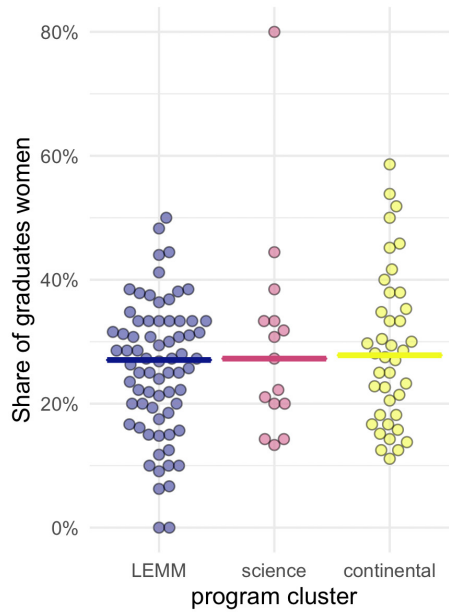


FIGURE 4 Distribution of gender by cluster. Each point represents one program included in the cluster analysis. Color and the x-axis indicate the program’s cluster; the y-axis indicates the share of graduates of the program who are women. Solid bars indicate the median across programs within the cluster. The medians are almost identical, and so at the cluster level there does not appear to be a substantial difference in gender of graduates from programs across these three clusters.

cluster median. There is substantial variation within each cluster in the share of women graduates, with some programs having less than 10 percent women graduates and others more than 40 percent. The medians are almost identical, however, at just below 30 percent, and so at the cluster level there does not appear to be a substantial difference in gender of graduates. At the level of individual respondents, Schwitzgebel and Jennings (2017, table 3) found a similar range of gender distributions across the four AOS categories.

The silhouette value for $k = 6$ (see Figure 2) indicates that this cluster solution is not quite as good as $k = 3$. Inspecting these clusters, however, adds some valuable nuance to the labels we have used above. While the “science” cluster remains the same (15 programs), both the “analytic” and the “continental” clusters have been split, at $k = 6$. On the “analytic” side, one cluster (58 programs) has the same analytic traits seen above: Analytic, AOS Metaphysics, Mind, Epistemology, and Metaphysics. But the other cluster (14 programs) has a somewhat counter-intuitive collection of traits: Aesthetics (1.56), AOS Mind (1.21), Cognitive Science (1.19), AOS Religion (0.83), and AOS Other (0.72). The majority of programs in this group specialize in scientifically informed philosophy of mind, and so sit in between the core analytic and philosophy of science groups, while the remainder have foci in some combination of aesthetics, mind, and religion. The lesson we take from this cluster is not that there is some hitherto overlooked Aesthetics-Mind-Religion tradition within philosophy but rather that the clustering algorithm is based on correlations observed in a limited dataset. We should be careful not to overinterpret these findings.

At $k = 6$ the “continental” cluster has split into three clusters. One, with 15 programs, has the same traits as the $k = 2$ and $k = 3$ “continental” cluster. A second cluster (17 programs) has traits Historical (1.26), Medieval (1.16), AOS 19th/20th (1.04), AOS Medieval/Renaissance (1.00), and Religion (0.93). And the third (8 programs) has traits AOS Applied Ethics (2.24), Gender/Feminist (1.87), Applied (1.40), Bioethics/Medical Ethics (1.27), and Political (0.97).

To us, this array of clusters suggests that the “continental” label from $k = 2$ might be an oversimplification. The $k = 2$ cluster seems to include not just “core continental” programs (phenomenology, 19th- and 20th-century French and German philosophy) but also work on the history of philosophy—especially the kind of historical work done at some religious-affiliated programs, such as the University of Notre Dame and Baylor University—as well as a practical, applied, feminist tradition. In short, and in line with the discussion above, this cluster analysis suggests that there are multiple, somewhat distinct “nonanalytic” traditions in anglophone academic philosophy.

Below, we use the $k = 3$ clusters in our regression analysis of job market outcomes. This choice is supported both quantitatively by the silhouette score and by the lack of counterintuitive clusters (e.g., Aesthetics-Mind-Religion). While we use the “continental” label, we do this out of convenience and encourage readers to remember that $k = 6$ indicates substantial heterogeneity within this cluster.

Figure 5 shows an alternative visualization of the relationship between clusters. In this figure, each point is a single program, colored by its $k = 3$ cluster; boundaries have been added to make it easier to identify the scope of each cluster. The points are arranged using *multidimensional scaling* (MDS), a technique that attempts to represent abstract “distance” relationships in Euclidean space. That is, the distances between points in this visualization should, on average, correspond to the correlation distance between programs that was used to construct the clusters. This visualization offers a perspective complementary to the cluster analysis, indicating substantial overlap between the analytic and continental clusters. The scientific cluster has some overlap with the analytic cluster but is more distinctive.

From these results, it is clear that the discipline can be divided in multiple ways at different levels of organization. At the coarser levels, the clusters seem to correspond to the conventional analytic-continental distinction. These coarse groups, however, are not the whole story: there is a distinct philosophy of science cluster, as well as suggestions of further distinguishable traditions outside analytic philosophy. Table A1 shows the highest- and lowest-scoring AOS and keywords for the $k = 6$ cluster solution. Table A2 in the appendix below lists all programs considered for the cluster analysis along with their assigned cluster in each of the three values of k .

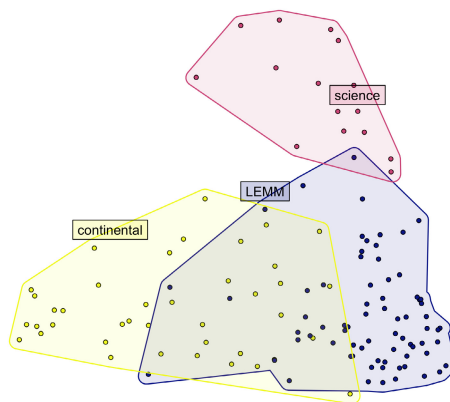


FIGURE 5 Visualization of clusters using multidimensional scaling (MDS). Each point represents a single program, colored by its $k = 3$ cluster. On average across all pairs, Euclidean distances between these points approximate the correlation distance between programs, used to construct the clusters.

4 | NETWORK ANALYSIS AND PRESTIGE

Prestige is said to be used by hiring committees across the academy to predict future performance, in place of past performance (Baldi 1995; Bedeian et al. 2010; Crane 1970; Kawa et al. 2019). Prestige is much easier to track than individual quality, such as by reading past publications or writing samples. Moreover, prestige may be a rough-grained measure of individual quality. It is not, however, a fine-grained measure. It thus will exclude some individuals with high-quality work and include others with low-quality work. Further, it may be that some of its value is illusory. That is, it may seem to be a better measure than it is simply because it is used as a potential indicator of success at every stage of one’s career, providing more opportunities for those connected to prestigious institutions.

For the above and other reasons, De Cruz (2018) argues that “prestige bias” in philosophy is an obstacle to a just and inclusive discipline. Yet, De Cruz uses metrics of prestige (that is, Philosophical Gourmet Report rankings) that have been criticized in the past as misrepresenting some aspects of the discipline (Bruya 2015; Walker 2004). We wondered if we could determine the effect of prestige on hiring through use of the APDA data alone.

To this end, we used two separate methods to establish that prestige plays an important role in the hiring of job candidates into philosophy Ph.D. programs, finding a significant gap in prestige between those graduate programs that hire from all other programs (low-prestige programs) and those graduate programs that tend to hire only from a select group (high-prestige programs; see Figure 6). Yet, this gap did not extend to academic hiring in general. That is, there is substantial overlap in the placement rates of high-prestige and low-prestige programs, indicating that universities that do not offer a Ph.D. in philosophy are not restricting themselves to the select group of high-prestige programs (see Figure 10). In fact, some high-prestige programs, which are *more* likely to have graduates hired at other high-prestige programs, are also *less* likely to have graduates hired overall. This fits accounts of prestige bias among A-list celebrities: “Highly ranked film stars exhibit homophily through a very tightly connected network upheld by attending the same high-profile events with each other” (Ravid and Currid-Halkett 2013). In other words, A-list celebrities are thought to maintain their elevated status by excluding other celebrities, widening the perceived gap between these groups. This might likewise explain the stark divide we see between high-prestige and low-prestige programs—it may be an artifact of the gatekeeping work of high-prestige programs in an effort to maintain their high-prestige status.

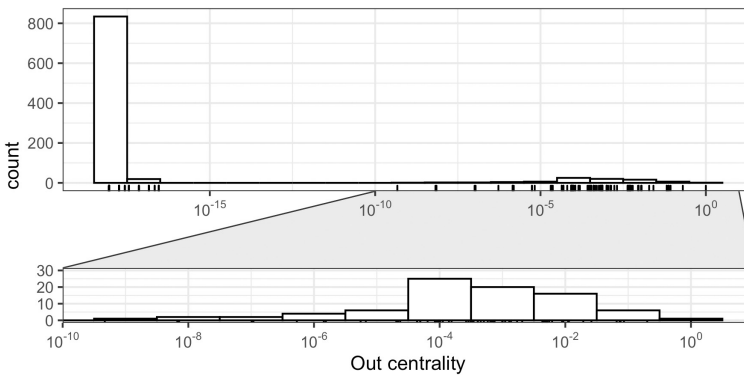


FIGURE 6 Histogram of prestige (eigenvector centrality) scores. Greater values on the horizontal axis (closer to 1, farther right) indicate greater centrality or higher prestige. There is a large gap between about 10^{-15} and 10^{-10} , sharply dividing programs into two groups. The lower panel shows the same data, zoomed in on the high-prestige group.

4.1 | Methods

We conducted a network analysis of permanent academic placements (including but not limited to tenure-track hires), using data on 3,448 2012–2019 graduates with known institutional affiliations (both placing and hiring, academic and nonacademic) whose most recent placement was in 2012 or later, as of the data pull on 18 August 2021.⁷ Of these Ph.D. holders, 1,809 (52 percent) had a permanent academic placement. These individuals received their Ph.D.s from 220 programs; 179 programs had graduates with permanent academic placements. Including all hiring institutions for permanent academic placements gives a total of 936 academic institutions in the hiring network. Only the most recent placement was used for each individual.

For this analysis, we represented programs as nodes, connected by individual Ph.D. holders as edges. Edges are directed: an individual received a Ph.D. from one program (the *placing* program) and works at another (the *hiring* program). Programs can be connected by multiple edges, representing multiple hires from the same placing program; and programs can have loops or self-connecting edges, representing individuals who are hired at the university where they received their Ph.D. Both of our measures of prestige accounted for directionality, multiple edges, and loops.

With the exception of certain history and philosophy of science (HPS) programs, affiliations are tracked only at the university level.⁸ Thus, while a philosopher of science might sometimes be hired by a science and technology studies (STS) program rather than a philosophy department, or a bioethicist might be hired by a university's medical school, this level of detail isn't captured in the data. For this analysis, we assume that any Ph.D.-holding philosopher in any permanent position at a given university is likely to work with philosophy graduate students in some capacity, participate in the philosophy program's colloquia and other events, publish under their university affiliation, and in other respects contribute to both the intellectual formation of the Ph.D. program's graduate students and the prestige of the Ph.D. program. So, with the exception of the HPS programs identified above, we identify a university with its philosophy Ph.D. program and use the terms "university" and "program" interchangeably.

We used methods from social network analysis to measure the relative "importance" or "prestige" of philosophy Ph.D. programs in the hiring network. Note that in this study we treat "prestige" as a thin or purely descriptive term. In particular, we do not assume that prestige is justified by the quality of research done by the faculty and graduate students of a particular program, in any sense. Instead, in this paper prestige simply reflects who hires whom—which graduate students are placed into which hiring programs. We discuss the evaluative aspects of prestige below.

For this study, we propose that *prestigious Ph.D.-granting programs are those whose students are hired at other prestigious Ph.D.-granting programs*. As a conceptual model, suppose programs are arranged on a ladder, with the most prestigious programs at the top. Prestige bias means that, all else being equal, hiring committees would prefer to hire graduates from more prestigious programs, higher up on the ladder. In particular, they would like to hire graduates from programs more prestigious than their own program, in the hopes that this will increase their own prestige. Further, the academic job market in philosophy is a buyer's market: there are more graduates from highly prestigious programs than there are open positions at highly

⁷Our construction and analysis of this hiring network made heavy use of the `igraph` (Csárdi 2019), `tidygraph` (Pedersen 2019), and `ggraph` (Pedersen and RStudio 2019) packages.

⁸The history and philosophy of science (HPS) programs are those at Arizona State University, Indiana University, UC Irvine, University of Cambridge, University of Chicago, and University of Pittsburgh.

prestigious programs. So graduates will tend to move down the ladder, being placed at programs less prestigious than the one that granted their Ph.D. The most prestigious programs will therefore be the ones that can successfully place their students in the most prestigious programs: the programs that are high on the ladder are the ones that are able to place their graduates high on the ladder.

We examined two ways of operationalizing this model of prestige on the hiring network and show below that they coincide.

In network analysis, “centrality” refers to any measure of importance on a network. Our first approach to measuring prestige uses one common measure, called *eigenvector centrality*. This approach allowed us to use standard software to calculate eigenvector centrality and thereby estimate the prestige of every program in the hiring network. (Any network can be represented as a matrix, where the entries of the matrix indicate whether two nodes—in our case, philosophy programs—are connected—in our case, by a graduate moving from their Ph.D. program to a permanent placement. This conception of prestige can be written as an equation in matrix algebra, and the solution to this equation—called the eigenvector of the matrix—gives the prestige score for each program.)⁹ Eigenvector centrality has frequently been used in analyses of academic hiring networks. Burris (2004) used eigenvector centrality, conceptualized as a measure of “social capital,” in an analysis of the hiring networks in sociology, history, and political science. Burris found that eigenvector centrality accounts for more than 80 percent of the variance in program prestige, as measured using a survey of academic sociologists. Clauset and collaborators have used a method that is conceptually similar to eigenvector centrality, but implemented in custom software, to study scholarly prestige hierarchies and their effects on the diffusion of research topics in computer science (Clauset, Arbesman, and Larremore 2015; Morgan et al. 2018).

Our second approach to operationalizing our conception of prestige involved starting with a single program—taken as an exemplar of a prestigious program—and backtracked through the network, identifying every program whose students are placed at the starting program, every program whose students are placed in those programs, and so on, until we reached a closed subnetwork. In other words, every program in this subnetwork has hired only from other programs within the subnetwork. We call this the *ancestor approach* to measuring prestige in the hiring network.

To implement this second approach in our study, we used New York University as our starting point. Certain informal surveys of graduate programs in academic philosophy have rated New York University as the most prestigious program in the United States. New York University also had a high eigenvector centrality in our first approach. We show below that

⁹Because of mathematical properties of eigenvectors, the scale of these prestige scores is arbitrary; the ratio of scores for two programs is meaningful, but the difference between them is not. The scale is set by convention, fixing the largest prestige score (that is, of the most prestigious school) at 1. More formally, let $A = (a_{ij})$ be the (directed) adjacency matrix: a_{ij} is the number of Ph.D.s from program i who were hired at program j . Let x_i be the centrality or prestige of university i , where a greater score indicates more centrality or prestige. Our proposal is that x_i is equal to the sum of the centralities x_j of every program that hires students from program i , weighted by the number of such students, times some scaling factor κ . That is,

$$x_i = \kappa \sum_{j \in I} a_{ij} x_j \tag{1}$$

$$x = \kappa Ax. \tag{2}$$

This implies that x is an eigenvector of the matrix A with eigenvalue $\lambda = 1/\kappa$. The Perron-Frobenius theorem implies that there is a unique value of λ whose eigenvector x is non-negative: that is, $x_i \geq 0$ for all nodes i . If x is an eigenvector of A with eigenvalue λ , and c is any scalar, then $A(cx) = cAx = c\lambda x = \lambda cx$, and so cx is also an eigenvector of A with eigenvalue λ . So eigenvectors are only unique up to multiplication by a scalar.

these two approaches coincide, allocating the programs to high-prestige and low-prestige groups in the same way.

4.2 | Results

Figure 6 shows the distribution of eigenvector centrality scores on a logarithmic scale. The scores have been normalized so that 1, on the right edge of the plot, is the maximum possible score (maximum prestige).

The vast majority of programs have a score of 10^{-15} or smaller (at the left end of the figure); this means that the vast majority of programs have relatively low prestige, as measured using the hiring network. In many cases this is because these programs produced no Ph.D. students, or none who were hired in a permanent position, during the time frame of this study. Because these programs have no outgoing edges in the hiring network, their centrality is within a rounding error of 0. Many Ph.D.-producing programs do appear, however, at the left end of the plot.

On the other hand, 83 programs have a centrality score of 10^{-10} or higher (at the right end of the figure); these programs are highlighted in the lower panel. No programs are found in the gap between 10^{-15} and 10^{-10} . In other words, *there is a sharp division in terms of prestige, with two strongly separated groups*. We classified the 83 programs above the gap (greater than 10^{-12}) as “high prestige” and the programs below the gap (less than 10^{-12}) as “low prestige.”¹⁰

These same 83 programs also form the closed set of “ancestors” of New York University, our second approach to operationalizing prestige (Figure 7). *This means that, in our data, these 83 programs only hired graduates from one another*. It is notable that the ancestor approach to identifying high-prestige programs agrees perfectly with the eigenvector centrality approach. By either approach, there is a sharp division between high- and low-prestige programs.

Eigenvector centrality also agrees with our conceptual model of graduates typically moving down the prestige ladder. Figure 8 shows the movement of graduates from placing to hiring programs. As the figure indicates, some graduates do move up, but relatively few, and only to slightly more prestigious programs. Most graduates move down as they are hired into permanent positions. This coincides with the aforementioned analysis by De Cruz (2018), which similarly found that there is very little upward mobility from placing to hiring programs.

Figure 9 helps us to understand how the topology of the hiring network influences prestige. A program’s total number of graduates with permanent placements is correlated with prestige; but the correlation is much weaker than might be expected. The figure shows the downstream placement networks for two large programs, Villanova University (17 permanent placements during the period of our analysis) and KU Leuven (23 permanent placements). Both are in the low-prestige group. When, however, one permutes the network (to examine how prestige status would be different if hiring patterns had been different), Villanova is much more likely to be in the (counterfactual) high-prestige group. This is because Villanova has a much larger downstream network, including several other Ph.D. programs with a fair number of graduates. In these scenarios, if any of these downstream graduates secures a permanent position

¹⁰We are not interested here in producing rankings of programs, and we do not believe that “prestige” status necessarily reflects a distinction of merit or quality of programs. We discuss these points further below. For these reasons, we have chosen to downplay the identity of the 83 particular programs included in the high-prestige group. While many of the names of these programs can be seen in figure 7, we do not provide a complete list or table of these programs. In addition, because of the properties of eigenvectors, the difference between scores is not meaningful. So, rather than interpreting the scores directly, we focus our interpretation on the dichotomy of high versus low prestige.

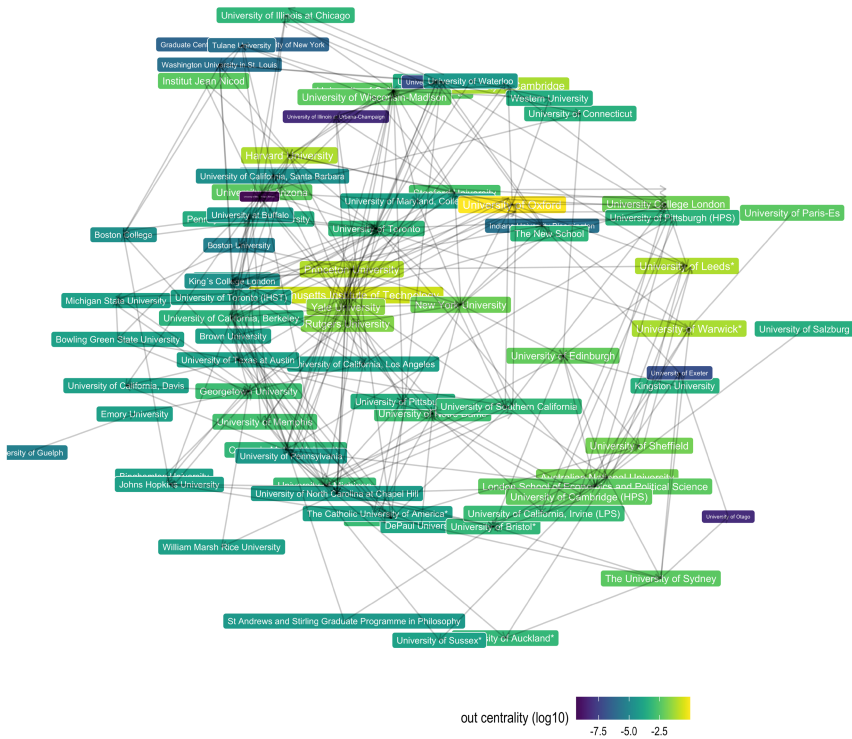


FIGURE 7 The high-prestige subnetwork. Node color and font size indicate centrality/prestige. The University of Oxford, in the lightest color and just up and right of center, has the highest prestige; the University of Massachusetts, Amherst, in the darkest color and to the left of Oxford, has the lowest prestige within this high-prestige subnetwork. New York University, in the center, was used as the basis for the ancestor approach to identifying this subnetwork. Because we do not believe that “prestige” status necessarily reflects a real distinction of merit or quality of programs, we wish to downplay exactly which programs are included in this subnetwork.

at a high-prestige program, all the upstream programs move to the high-prestige group. For example, if a CU Boulder graduate were to secure a high-prestige position (and the links connecting Villanova to Boulder were not changed in the permutation), Villanova would be in the high-prestige group. In contrast, KU Leuven has a much smaller downstream network, limiting its opportunities to move to the high-prestige group. So prestige depends not just on where a program places its graduates but also on where those downstream programs place their graduates, and so on.

Figure 10 shows the permanent placement rate for each program, with distributions and medians for each prestige group. Permanent placement rate is the fraction of all graduates from a Ph.D. program who have a permanent academic position in the data.¹¹ The median permanent placement rate is higher for high-prestige programs than for low-prestige programs (58 percent versus 39 percent). Figure 10 also indicates substantial variation within each prestige group, however. Some small low-prestige programs have 100 percent permanent placement rates, and a number of larger low-prestige programs are around or above 65 percent. At the same time, a number of

¹¹Note that the total number of graduates does not include those who have no or unknown placement in these analyses. Further, because we do not have information on whether nonacademic positions are permanent, they are conservatively counted as nonpermanent for this calculation. In any case, nonacademic placements make up only around 5 percent of all placements in the APDA database.

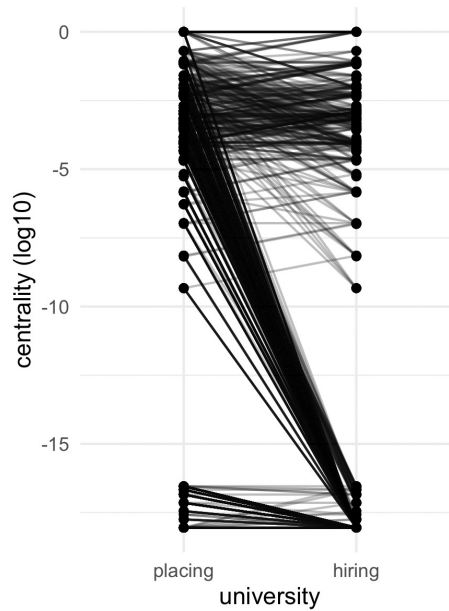


FIGURE 8 The movement of Ph.D.s down the “prestige ladder.” Each line represents an individual in the APDA dataset. The left endpoint is the centrality or prestige of the individual’s Ph.D. program; the right endpoint is the centrality or prestige of the individual’s most recent placement. Most lines slope downward, indicating that most individuals are hired at less prestigious programs than where they received their Ph.D. Most graduates of high-prestige programs (above 10^{-10}) are placed in low-prestige programs (below 10^{-15}).

high-prestige programs are below 50 percent, including a few around 25 percent. The graph in [Figure 10](#) suggests that while graduating from a high-prestige program might improve one’s chances on the academic job market, clearly it does not guarantee a position. We discuss the magnitude of this prestige effect in the context of our regression analysis below.

In summary, using purely topological features of the academic hiring network in philosophy, our analysis finds a clear division of Ph.D. programs into two groups, which we label “high prestige” and “low prestige.” This division agrees with several assumptions about the effects of prestige of career placement, and so seems to capture an intuitive understanding of prestige.

4.3 | Discussion

The division of academic philosophy into high-prestige and low-prestige groups should not necessarily be interpreted as a measure of merit or quality, at either the program level or the individual level. Sociologist of science Robert Merton coined the term *the Matthew effect* for a cumulative advantage process in scientific careers: scientists who started with greater resources and recognition than their peers will tend to be more productive and influential, and so receive still greater resources and recognition over time, leading to a widening gap between the academic “haves” and “have-nots” (DiPrete and Eirich 2006; Merton 1968).

Critically, the Matthew effect is not based on any initial difference in quality or merit; a scientist may end up in the “have” or “have-not” group purely as a matter of luck. Similarly, Heesen (2017) constructs an *a priori* model of scientists reading one another’s papers during a single period of time. Briefly, scientists are constrained in the number of papers they can read, and they prefer to read higher-quality papers. The result is a highly unequal distribution of

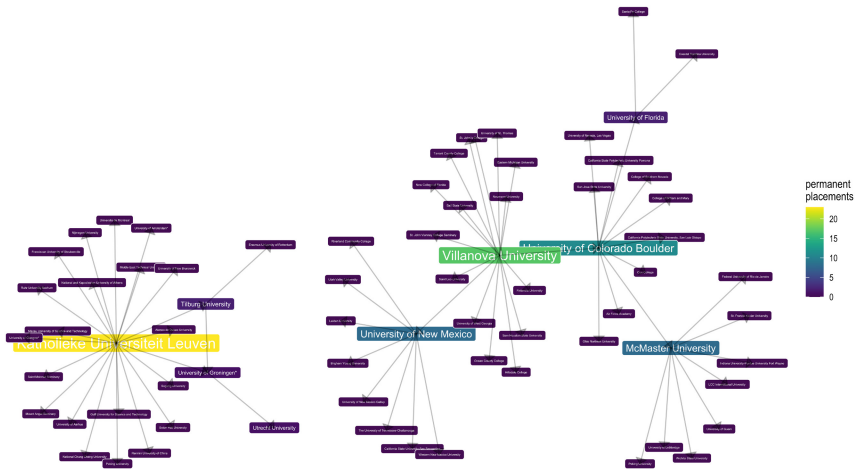


FIGURE 9 Network topology influences prestige. The figure shows downstream hiring networks for Villanova University (right) and KU Leuven. These two programs produce about the same number of Ph.D.s and are both in the low-prestige group. When, however, one considers counterfactual hiring networks, Villanova is much more likely to be in the high-prestige group, because of its larger downstream networks.

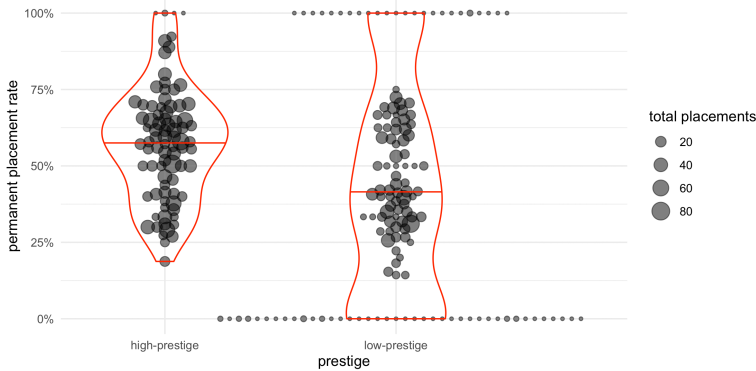


FIGURE 10 Permanent placement rate for each program, by prestige category. Point size indicates the number of Ph.D.s produced by each program. Violin plots (in curves) indicate distributions and medians within each prestige category. The high-prestige group has a higher median placement rate than the low-prestige group. Quite a few high-prestige programs, however, have placement rates of 50 percent or lower, and many low-prestige programs have placement rates greater than 50 percent.

attention or epistemic authority: a few authors are very widely read, while most authors have only a few readers. Heesen shows that this pattern can arise *either* because some authors tend to produce higher-quality papers than others (meritocracy), *or* because there is no difference in average quality or tendency, but certain authors simply got lucky and happened to produce higher-quality papers early on (pure luck), *or* because of a combination of these two processes. Using empirical data on faculty pedigree and productivity, Way, Morgan, Larremore, and Clauset find that “the prestige of faculty’s current work environment, not their training environment, drives their future scientific productivity, while current and past locations drive prominence” as measured by citations (2019, 1). That is, prestigious Ph.D. programs do not as such tend to produce more meritocratically accomplished faculty; rather, they tend to produce Ph.D.s who are more likely to be hired by prestigious institutions and given ample resources.

These empirical results suggest a strong role for luck and prestige effects, and a relatively weak role for meritocracy.

Consider applicants to graduate programs in philosophy. Suppose there is no difference in tendency—none of the applicants is, in any real sense, “better” than the others. But, purely through chance, some applicants happen to produce slightly better writing samples than others. They are, on this particular occasion, lucky. (Also supposing, of course, that there’s a straightforward matter of fact about the quality of writing samples.) The lucky applicants are more likely than the unlucky to receive admission offers from more prestigious programs (which, we suppose, are likely to be more selective than their lower-prestige peer institutions). These lucky applicants then have access to the greater resources possessed by these more prestigious programs—including effective opportunities to apply for jobs in other high-prestige programs. Again, by hypothesis there are no differences in quality between individuals, but luck and the Matthew effect could produce the kinds of differences in permanent placement rates and eigenvector centrality seen in [Figures 7 and 10](#).¹² For these reasons, we do not assume the differences we found in prestige correspond to differences in quality.

5 | REGRESSION ANALYSIS AND PERMANENT ACADEMIC PLACEMENT

APDA has collected placement information since 2011, publishing multiple research reports and blog posts on placement trends. One of the most surprising such trends has been the finding that women have been more likely to obtain permanent academic placement than men in recent years (see, e.g., [Jennings, Cobb, and Vinson 2016](#)).¹³ Women are underrepresented in philosophy, a fact that has received considerable attention ([Antony 2012](#); [Leslie et al. 2015](#); [Paxton, Figdor, and Tiberius 2012](#); [Thompson 2017](#)). In fact, “women’s involvement and visibility in mainstream Anglophone philosophy has increased only slowly; and by some measures there has been virtually no gain since the 1990s” ([Schwitzgebel and Jennings 2017](#), 83). The proportion of women among graduate students, for example, has stayed just under 30 percent for decades, while the proportion of women among faculty is somewhat lower, for example 25 percent in 2014 for 59 graduate programs in the United States ([Schwitzgebel and Jennings 2017](#), 89, 85). If women had been more likely to find permanent academic placement for some time, we would expect the proportion of women among faculty to be higher than the proportion of women among graduate students.

We decided to look at this issue once more, this time including more variables in our regression model. These include the cluster labels and prestige categories identified in previous sections of the present paper. We find, once again, that women have been more likely to find permanent academic placement in recent years. We also find effects of prestige and geography, the latter of which will require further exploration. Given these findings, we might expect the proportion of women among philosophy faculty to increase going forward, an investigation we leave to future work.

5.1 | Method

To explore the impacts of gender, prestige, and other factors on permanent academic placements, we used data on 2,778 2012–2019 graduates from 129 programs (those programs with

¹²[Schwitzgebel \(2019\)](#) provides evidence that undergraduate prestige effects also play a role in graduate admissions.

¹³This general finding has been published elsewhere through research reports and blog posts associated with the APDA project, but this is the first time it appears in a peer-reviewed journal.

data validated in 2021) whose most recent placement was in 2012 or later and for whom we had complete data on their AOS, graduation year, gender, institutional affiliation (both placing and hiring; academic placements only), and whether their most recent placement was permanent, as of the data pull on 18 August 2021. Only the most recent placement was used for each individual.¹⁴

Regression models are statistical models that attempt to describe functional relationships between a *response* variable—usually designated y —and one or more *covariates* or *predictor variables*—usually represented with an x . When interpreted causally, the coefficients associated with each covariate estimate the effect of that variable on the response as though all other covariates were held fixed (Morrissey and Ruxton 2018). For example, suppose gender and AOS category are correlated (Schwitzgebel and Jennings 2017, table 3). By including both in the same regression model, we effectively control for one in estimating the effect of the other, and vice versa. So the coefficient for gender is the effect of gender as though AOS category were held constant in an experimental setting.

Our model includes covariates at the level of both the individual Ph.D. holder and the Ph.D. program from which they graduated. The individual-level covariates are gender (women, compared to men), AOS category, graduation year, and the first year of the most recent position. The program-level covariates are a measure of AOS diversity, cluster (analytic, science, or continental, as identified above), logged hiring centrality (a network measure that complements the prestige analysis above), total number of placements in the data, the percentage of graduates who are women in the data, country (compared to the United States), and prestige category (high compared to low, as identified above). Our response variable is whether the most recent position is permanent or temporary.¹⁵

5.2 | Results and discussion

Some of the regression model results are not surprising: more recent graduates are less likely to be in a permanent position; there appears to be little difference between area of specialization categories; and Ph.D. program size does not influence an individual's chances of having a permanent position. Three results are more notable. (a) Women and (b) graduates of high-prestige programs appear to have a substantial advantage, roughly a 7–14 percent increase (prestige) and 10–17 percent increase (women) in the probability of landing a permanent position (within the time frame of the available data); while (c) philosophers who received their Ph.D. outside the United States are at a notable disadvantage compared to United States–trained philosophers. We discuss these findings and potential explanations for them below.

Figure 11 summarizes the data used in the model. In-centrality or hiring centrality measures the prestige of a given program's hires who are in the APDA dataset (that is, recent faculty hires). Country indicates the country in which the individual's Ph.D. program is located; it is a program-level variable, not an individual-level variable.

¹⁴These data are a subset of the data used for the network analysis above. The sample is smaller because (a) we are excluding both nonacademic placements and those with no placement on record and (b) we are only including individuals with complete data for all covariates. Network analysis results from the previous section—using the larger sample—were used for the program-level covariates.

¹⁵We implement a Bayesian random effects logistic regression model in the R and Stan languages using the `rstanarm` interface (Gabry et al. 2018; R Core Team 2021; Stan Development Team 2017). Weakly informative priors were chosen following recommended practice (Gelman et al. 2008). Further details are available upon request. MCMC convergence was assessed by inspecting effective n and \hat{R} statistics for every fitted parameter; \hat{R} was below 1.01 for every parameter, and effective n was at least 3,000 for every parameter except on the variation hyperparameter for graduation year ($n_{\text{eff}} = 2,945$). Model quality was assessed using posterior predictive checks, all of which closely matched the observed permanent placement rate.

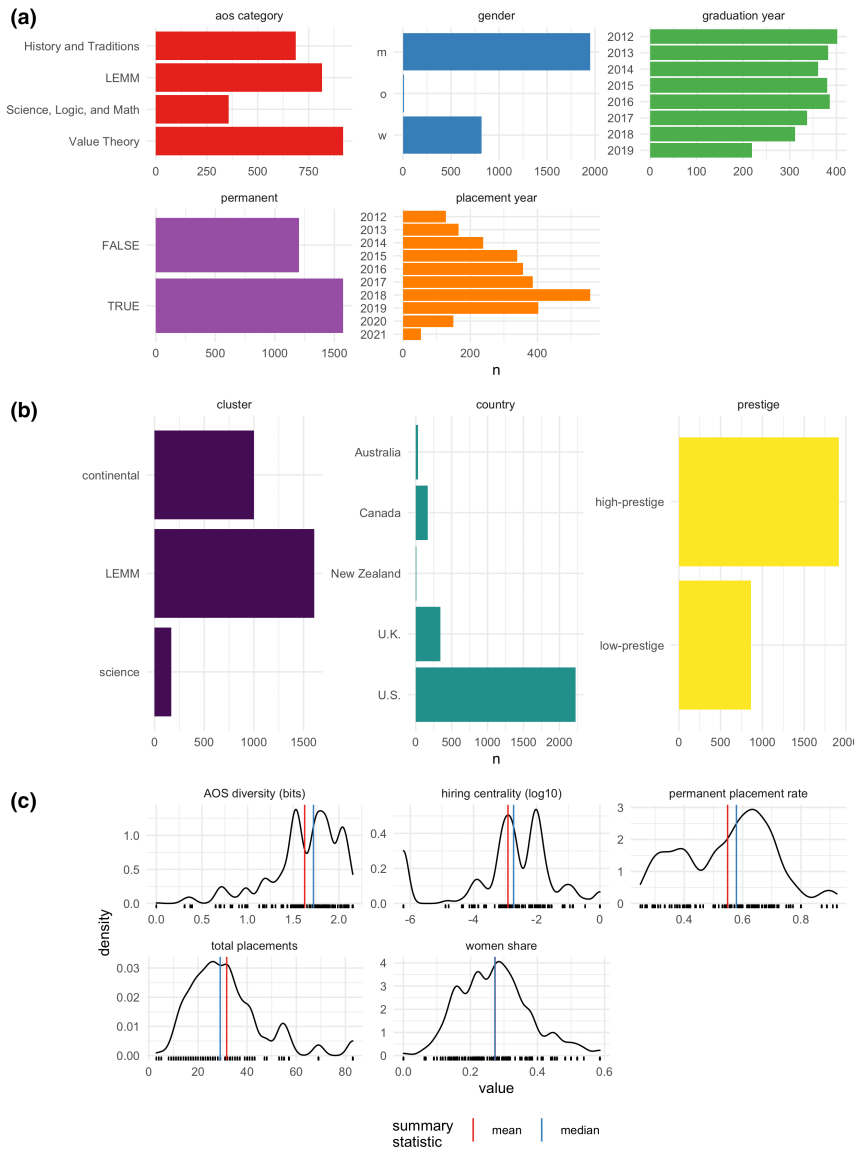


FIGURE 11 Data used in the regression model of placement outcomes. The dependent variable, permanent placement, is in the top panel. (a) Individual-level variables, all of which are discrete/categorical. (b) Program-level categorical variables. (c) Program-level continuous variables. In (b) and (c), counts are of individuals, not programs; for example, the number of individual graduates from analytic cluster programs.

Figure 12 shows estimates for all the coefficients and random effects in our regression model. All estimates in this figure are reported as a *multiplicative change in odds of permanent placement*, on a percentage scale. For example, a value of 50 percent means that the estimated effect is a 50 percent increase in odds, or multiplying the odds of permanent placement by 1.5; while a value of -20 percent means that the estimated effect is a 20 percent decrease, or multiplication by $1 - 0.2 = 0.8$. Worth noting is that translating odds to probability depends on the baseline, so when we report “probability differences” in the following, we are actually reporting average marginal effects.

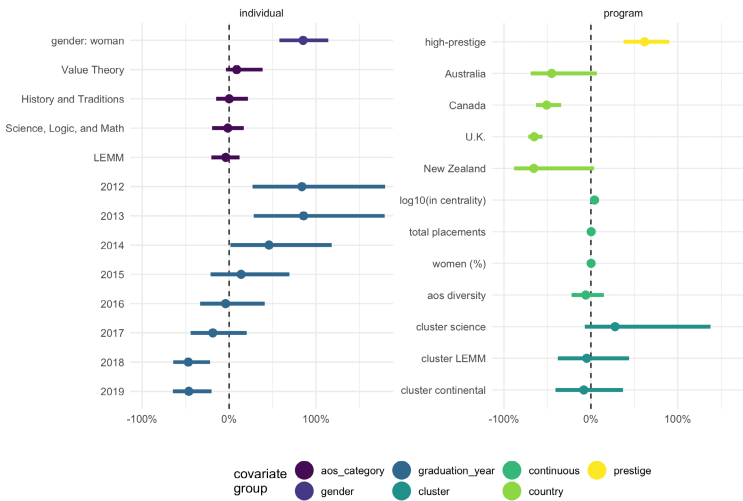


FIGURE 12 Regression coefficient and random effects estimates. Values are expressed as a multiplicative change in odds of permanent placement, on a percentage scale. For example, a value of 50 percent means that the estimated effect is a 50 percent increase in the odds, or multiplication by 1.5. Intervals are Bayesian 90 percent centered posterior intervals: the model is 90 percent confident that the true value is within the intervals. Estimates for placement year are not shown. Estimates for gender: woman, high-prestige program, and program country are relative to gender: man, low-prestige, and United States, respectively. Estimates for AOS category, graduation year, and program cluster are random effects and not comparative.

Gender. Gender effects are relative to men. Because there is only a single “other” individual in the data, the estimate for this group is highly uncertain and not reported. The model estimates that women have 58–114 percent greater odds than men, or a probability difference of 10–17 percent.

This finding is highly counterintuitive. As discussed above, women are significantly underrepresented in philosophy, constituting 26 percent of faculty in a 2011 survey (Paxton, Figdor, and Tiberius 2012) and 30–34 percent of new Ph.D.s in philosophy awarded to women annually over the past several decades (Schwitzgebel 2017). There is some debate over the causes of this persistent underrepresentation (see, e.g., Antony 2012), but a number of authors have identified as likely factors implicit bias (Lee 2016; Régner et al. 2019) and more generally a less welcoming or more hostile environment toward women and other underrepresented groups (Settles and O’Connor 2012). Yet factors such as implicit bias should give women a disadvantage in the academic job market, which, again, is not what our analysis shows.

Some potential explanations for women’s apparent advantage are already addressed by our regression analysis: because we control for individuals’ rough areas of specialization, the prestige of their graduate programs, and spatial and temporal patterns (that is, country of origin and graduation year), women’s advantage cannot likely be explained by these factors. Another possibility is that women have, on average, greater aptitude for philosophy than do men by the time they reach the job market. The greater attrition faced by women at earlier stages in their career may lead to the remainder having higher average aptitude when they are on the job market. Alternatively, if women are held to higher standards than men at earlier stages in their career, perhaps that leads to greater learned aptitude. Analyzing articles in major economics journals, Hengel (2022) finds that women tend to become better writers than men (according to technical measures of readability) as their careers develop, and that women’s papers tend to spend longer time in peer review. Combining these observations, Hengel argues that women are held to higher standards than men in peer review and suggests that women

gradually internalize these higher expectations (see also Bright 2017; Leuschner 2019). It isn't clear, however, that these findings can explain the effect found here. The effect that Hengel identifies appears gradually over several years; in their first few publications, there is no difference in readability on average between women and men. But this is also the period when most applicants are on the academic job market. Applying Hengel's model to the academic job market in philosophy would seem to require a similar gender-linked aptitude difference appearing much earlier than Hengel finds in economics publishing.

A more optimistic potential explanation is that, in recent years, hiring committees and others have taken steps to remediate underrepresentation and its most likely causes. For example, hiring committees might conduct a search in subfields with a greater share of women and other underrepresented groups, such as feminist philosophy, and then might adopt strategies for reviewing applications and conducting interviews that are designed to block implicit bias. Other changes, such as the shift from hotel rooms to videoconferencing for first-round job interviews, might have the side effect of reducing discriminatory processes against women, even if they weren't adopted with this intention. But even if these kinds of changes have successfully mitigated factors that work against women, it is hard to see how they would give women a substantial net advantage. It may be that, all else being equal, hiring committees tend to prefer women candidates.

Finally, we note that this gender effect is likely to be a recent development. As mentioned above, women have received 30–34 percent of new Ph.D. degrees in philosophy for decades, but in the past decade have made up only 19–26 percent of philosophy faculty (Schwitzgebel and Jennings 2017). If women had this placement advantage over men for several decades, we would expect women to be better represented among faculty than new Ph.D.s. For example, suppose there were 100 new Ph.D.s in a given year, 35 of which were women (35 percent) and the remaining 65 men. If 66 percent of the men and 77 percent of the women secured a permanent position (a 10-point probability difference), the new faculty would have 43 men and 27 women (rounding to the nearest whole number), or 39 percent women.

All together, while our analysis finds that women are hired at greater rates in the academic job market in philosophy, it is not clear what might explain this difference, and it is likely to be a recent development. Moreover, we emphasize that this finding is entirely compatible with the existence of a hostile climate, implicit bias, and other factors that drive women (and other gender and sexual minorities) away from academic philosophy. For example, in a 2012 survey conducted by the Philosophy of Science Association, respondents who identify as women found the climate of both the PSA Biennial Meeting and the discipline as a whole to have a less welcoming, more sexist, less diverse, and more exclusionary climate, with more incivility and harassment, compared to respondents who identify as men (Settles and O'Connor 2012, table 6). Furthermore, Dowell and Sobel (2019) separately summarize the evidence showing that sexual harassment is pervasive across academia. Among other points, they note that 15 out of 655 publicly documented cases of sexual harassment in the “Not a Fluke” database are in philosophy, and that 4 out of 15 high-profile cases examined by Martinez (2017) involved philosophers.¹⁶

Prestige. The prestige effect for high prestige is relative to low prestige. Controlling for other factors in the model, graduates of high-prestige programs have 38–90 percent greater odds than graduates of low-prestige programs, or a probability difference of 7–14 percent. This is not trivial, but it is also smaller than we expected before starting this project. Many early career scholars express anxiety and regret about their job prospects if they did not graduate from a “top-ten program” (for examples from APDA survey comments, see Jennings 2021a, 2021b, 2021c). Our analysis indicates that prestige is a factor, but also that there is large variation in

¹⁶As of December 19, 2019, the “Not a Fluke” database has been available at <https://academic-sexual-misconduct-database.org>. At least 20 out of the 1,006 (2 percent) included cases are in philosophy. For comparison, philosophy Ph.D. students make up less than 1 percent of all Ph.D. students in the United States (477 of 55,195 in 2018 according to the National Science Foundation's Survey of Earned Doctorates).

placement rates within the two prestige categories. Prospective graduate students concerned about their academic job prospects should look at the actual placement history of particular programs, and not rely solely on prestige as a proxy.

This does not mean that the prestige hierarchy in academic philosophy is benign. We expect that it plays a significant role in the distribution of resources and influence across the discipline, in ways that go beyond the job market data available in this study.

Country. All country effects are relative to the United States. The model finds a notable disadvantage for every non-U.S. country included in the data. For example, the probability difference for the United States versus Canada is 9–22 percent.

Because only anglophone programs have validated data, this disadvantage is probably not due to language barriers.¹⁷ This finding also cannot be explained by the prestige of programs in these countries, and program prestige plausibly includes name recognition effects. For example, U.S. faculty might be less familiar with programs outside the United States and discount job applications from graduates of such programs, but insofar as this effect is likely captured by prestige, and the model controls for prestige, this familiarity cannot explain these results.

It is unlikely that this finding is explained by recording errors or other methodological problems, but it may be explained in part by gaps in data coverage. While the titles for permanent positions can vary across countries (for example, “lecturer” is usually a nonpermanent title at U.S. universities but a permanent and higher-level one in the United Kingdom), APDA personnel are explicitly trained on this issue when recording data. Moreover, the method for data gathering is the same for the United States and other countries: APDA personnel look for dissertation records to determine all graduates of a program and then use search engines to find placement information, supplementing their findings with placement pages and other sources of data. Yet, programs outside the United States are less likely to have dissertation records and placement pages, making it more difficult to find the relevant information.

Perhaps more important, graduate training is markedly different between the United States and other countries; while a Ph.D. takes longer to complete in the United States, it comes with more coursework requirements and more teaching experience, which may lead to faster placement into permanent academic jobs. Moreover, the anglophone academic job market in philosophy is focused on the United States, in part due to the sheer number of philosophy programs in the United States, which may create structural disadvantages for job applicants coming from abroad. These may include anything from differences in networking opportunities, given the greater cost of travel, to differences in immigration and visa requirements, making it more difficult for those outside the United States to participate in the U.S. job market. And after receiving a job offer foreign applicants might find it difficult to relocate their families; specifically, taking a faculty job in the United States might require one’s partner to give up their career.

6 | SUMMARY AND CONCLUSION

We started out with some general questions about academic philosophy: To what extent can the discipline be divided into subfields with different methods and topics? How are prestige and credit distributed across the discipline? And how do these factors interact with other factors, such as gender, to shape job market outcomes? To answer these, we applied computational methods to the most complete dataset of doctoral graduates in philosophy over the past

¹⁷Language might yet be a factor for Canadian programs, insofar as francophone Canadians might study at an anglophone program—and so be counted in the denominator of the permanent placement rate—but then secure a permanent position at a francophone institution—and so be missed in APDA’s data-checking process and not be counted in the numerator.

ten years. This combination of new computational methods and a nearly comprehensive dataset allowed us to gain new insights about academic philosophy, which we summarize below.

First, the timeworn analytic-continental divide should be replaced with a three-way split, between analytic, continental, and philosophy of science programs. This three-way split provides a better overall grouping structure than the two-way split and sheds light on what is a highly unified set of programs—the philosophy of science group has minimal overlap with the analytic and continental groups and should be considered a distinct entity.

Moreover, the label “continental” is a poor fit, as can be clearly seen through the six-way split—this group includes a subset of programs focused on historical philosophy as well as a subset focused on applied and sociopolitical philosophy. Neither the historical nor the applied subset include “continental” as a top AOS or keyword. Thus, we suggest understanding this as a three-way split involving analytic philosophy, philosophy of science, and historical/continental/applied philosophy.

Second, we explored prestige and its impact on placement using two separate methods. Both methods revealed a stark divide between graduate programs that have hired exclusively from one another, on the one hand, and all other programs, on the other.¹⁸ We thus see a clear divide between high-prestige and low-prestige programs in the data. As mentioned above, this is evocative of the distinction between A-list and B-list celebrities, as described by Elizabeth Currid-Halkett: “Being a B-lister isn’t a stop on the way to A-list status. B-list stars are viewed as less talented than A-listers and, as such, B-list stars don’t graduate into A-list status. They stay in the middle rung and therefore don’t have the same opportunity to maximize their careers. . . . A B-lister must take a quantum leap into A-list status rather than plodding along a linear path, which is why it’s often the case that once a B-lister, always a B-lister” (2010, 109). Similarly, it may take a “quantum leap” for a program to move from low- to high-prestige status, a possibility we leave to future research with data over a longer period of time.

While individual graduate programs may maintain this distinction in prestige, it has less impact on programs overall. That is, if we look at placement rate across all philosophy programs, going beyond graduate programs, we see significant overlap in the placement rates of high-prestige and low-prestige programs. Thus, low-prestige programs may not be able to place graduates in high-prestige programs, but they may nonetheless be more successful at placing their graduates than many high-prestige programs. High-prestige programs do, however, have a higher *average* placement rate than low-prestige programs, indicating that prestige does have an impact on placement across the board.

Third, we explored the impact of gender on placement, among other factors, using a linear regression model. We find both women and graduates of high-prestige programs to have higher likelihood of permanent placement. Because we included factors such as area of specialization category, year of graduation, geographic location, and program cluster, we have ruled out many possible explanations of this finding. Yet, what makes this a surprising finding also points to it being a recent development in the field: the proportion of women serving as philosophy faculty is still remarkably low, and it would be much higher if this effect of gender on placement were a long-standing one.

We also found in our regression analysis a decreased likelihood of permanent placement for programs outside the United States. While APDA has aimed to have international coverage, availability of data in other countries may have limited its reach. On the other hand, it is possible that graduates of other countries have a more difficult time on the job market, which should be explored in future studies.

¹⁸Of course, one of these programs may hire from a program outside the group at some point. Moreover, it is possible that one of these programs hired from outside the group prior to this ten-year period or hired someone missed by the APDA project within this ten-year period. None of these possibilities would change the overall finding.

These findings are just the beginning for a science of science approach to philosophy. Philosophy is often imagined as a solitary exercise by individual scholars, but academic philosophers are guided by and guide others, taking part in various social networks of the field. A greater understanding of subfields and clusters, prestige effects, and hiring trends should enable philosophers to recognize and adjust their role in these networks. We hope to see further exploration of the findings provided here, but also of ideas as to how to apply these findings for the betterment of the discipline. For example, rather than seeing the aim of philosophy programs as covering all areas of philosophy, perhaps we should recognize and promote some degree of modularity. Programs might aim to discover, amplify, and advertise the traits that mark them out, using language common to the field. Similarly, rather than relying on the heuristics of prestige and celebrity, we might consider more carefully what makes for quality in philosophical methodology and practice.

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APPENDIX: TABLES

TABLE A1 Highest- and lowest-scoring AOS and keywords for k = 6 clusters

AOS/keyword	Side	Z-score
<i>Cluster 1</i>		
top	Analytic	0.59
top	AOS Metaphysics	0.43
top	Mind	0.39
top	Epistemology	0.38
top	Metaphysics	0.34
bottom	Interdisciplinary	-0.31
bottom	AOS Continental (inc. Phenomenology)	-0.34
bottom	Critical Theory	-0.34
bottom	Pluralist	-0.40
bottom	Continental	-0.50
<i>Cluster 2</i>		
top	Aesthetics	1.56
top	AOS Mind	1.21
top	Cognitive Science	1.19
top	AOS Religion	0.83
top	AOS Other	0.72
bottom	Historical	-0.44
bottom	Early Modern	-0.46
bottom	German	-0.47
bottom	Metaphysics	-0.47
bottom	Phenomenology	-0.50
<i>Cluster 3</i>		
top	Biology	2.18
top	AOS Science (General)	1.88
top	AOS Biology (incl Environmental)	1.71
top	History and Philosophy of Science	1.44
top	Naturalist/Empirical	1.42
bottom	Phenomenology	-0.50
bottom	Contemporary	-0.52
bottom	Mind	-0.57
bottom	Ancient	-0.58
bottom	AOS Ethics	-0.65
<i>Cluster 4</i>		
top	Historical	1.26
top	Medieval	1.16
top	AOS 19th/20th	1.04
top	AOS Medieval/Renaissance	1.00

TABLE A1 (Continued)

AOS/keyword	Side	Z-score
top	Religion	0.93
bottom	Contemporary	-0.40
bottom	Gender/Feminist	-0.40
bottom	AOS Mind	-0.42
bottom	Logic/Formal	-0.47
bottom	Naturalist/Empirical	-0.53
<i>Cluster 5</i>		
top	AOS Continental (inc. Phenomenology)	2.03
top	Phenomenology	1.83
top	Continental	1.77
top	French	1.56
top	Critical Theory	1.54
bottom	Mind	-0.60
bottom	History and Philosophy of Science	-0.61
bottom	Metaphysics	-0.62
bottom	Epistemology	-0.77
bottom	Analytic	-1.00
<i>Cluster 6</i>		
top	AOS Applied Ethics (inc. Bio. and Medical)	2.24
top	Gender/Feminist	1.87
top	Applied	1.40
top	Bioethics/Medical Ethics	1.27
top	Political	0.97
bottom	Metaphysics	-0.54
bottom	Early Modern	-0.55
bottom	Logic/Formal	-0.57
bottom	Naturalist/Empirical	-0.60
bottom	Analytic	-0.69

TABLE A2 Programs and clusters (programs are listed alphabetically within their k = 6 cluster)

Name	K = 2	K = 3	K = 6
Arizona State University	1	1	1
Australian National University	1	1	1
Brown University	1	1	1
Cornell University	1	1	1
Florida State University	1	1	1
Harvard University	1	1	1
Indiana University, Bloomington	1	1	1
King's College London	1	1	1
Massachusetts Institute of Technology	1	1	1

TABLE A2 (Continued)

Name	K = 2	K = 3	K = 6
New York University	1	1	1
Ohio State University	1	1	1
Princeton University	1	1	1
Rutgers University	1	1	1
St Andrews and Stirling Graduate Programme in Philosophy	1	1	1
Stanford University	1	1	1
Syracuse University	1	1	1
University at Buffalo	1	1	1
University College London	1	1	1
University of Alberta	1	1	1
University of Arizona	1	1	1
University of California, Berkeley	1	1	1
University of California, Irvine	1	1	1
University of California, Los Angeles	1	1	1
University of California, Santa Barbara	1	1	1
University of California, Santa Cruz	1	1	1
University of Cambridge	1	1	1
University of Colorado, Boulder	1	1	1
University of Connecticut	1	1	1
University of Florida	1	1	1
University of Georgia	1	1	1
University of Illinois at Chicago	1	1	1
University of Iowa	1	1	1
University of Kansas	1	1	1
University of Kentucky	1	1	1
University of Massachusetts, Amherst	1	1	1
University of Miami	1	1	1
University of Michigan	1	1	1
University of Missouri	1	1	1
University of Nebraska, Lincoln	1	1	1
University of North Carolina at Chapel Hill	1	1	1
University of Otago	1	1	1
University of Oxford	1	1	1
University of Pennsylvania	1	1	1
University of Pittsburgh	1	1	1
University of Reading	1	1	1
University of Rochester	1	1	1
University of Southern California	1	1	1
University of Tennessee	1	1	1
University of Texas at Austin	1	1	1
University of Toronto	1	1	1

TABLE A2 (Continued)

Name	K = 2	K = 3	K = 6
University of Virginia	1	1	1
University of Wisconsin—Madison	1	1	1
University of York	1	1	1
Victoria University of Wellington	1	1	1
Wayne State University	1	1	1
Western University	1	1	1
William Marsh Rice University	1	1	1
Yale University	1	1	1
Graduate Center of the City University of New York	1	1	2
McGill University	1	1	2
Temple University	1	1	2
University of Arkansas	1	1	2
University of British Columbia	1	1	2
University of California, San Diego	1	1	2
University of Edinburgh	1	1	2
University of Maryland, College Park	1	1	2
The University of Manchester	1	1	2
University of Nottingham	1	1	2
University of Oklahoma	1	1	2
University of Waterloo	1	1	2
Washington University in St. Louis	1	1	2
York University	1	1	2
Arizona State University (HPS)	1	2	3
Carnegie Mellon University	1	2	3
Duke University	1	2	3
Indiana University Bloomington (HPS)	1	2	3
London School of Economics and Political Science	1	2	3
University of Calgary	1	2	3
University of California, Davis	1	2	3
University of California, Irvine (LPS)	1	2	3
University of Cambridge (HPS)	1	2	3
University of Chicago (CHSS)	1	2	3
University of Cincinnati	1	2	3
University of Pittsburgh (HPS)	1	2	3
University of South Carolina	1	2	3
University of Toronto (IHST)	1	2	3
University of Utah	1	2	3
Baylor University	2	3	4
Boston University	2	3	4
The Catholic University of America	2	3	4
Columbia University	2	3	4

(Continues)

TABLE A2 (Continued)

Name	K = 2	K = 3	K = 6
Fordham University	2	3	4
Johns Hopkins University	2	3	4
Marquette University	2	3	4
Northwestern University	2	3	4
Purdue University	2	3	4
Saint Louis University	2	3	4
Tulane University	2	3	4
University of California, Riverside	2	3	4
University of Chicago	2	3	4
University of Dallas	2	3	4
University of Illinois at Urbana-Champaign	2	3	4
University of Notre Dame	2	3	4
University of South Florida	2	3	4
Boston College	2	3	5
DePaul University	2	3	5
Duquesne University	2	3	5
Emory University	2	3	5
Loyola University, Chicago	2	3	5
The New School	2	3	5
Southern Illinois University	2	3	5
Stony Brook University	2	3	5
Texas A & M University—College Station	2	3	5
University of Hawai'i at Manoa	2	3	5
University of Memphis	2	3	5
University of New Mexico	2	3	5
University of Oregon	2	3	5
Villanova University	2	3	5
Binghamton University	2	3	6
Bowling Green State University	2	3	6
Georgetown University	2	3	6
Michigan State University	2	3	6
University at Albany	2	3	6
University of Sheffield	2	3	6
University of Washington	2	3	6
Vanderbilt University	2	3	6