Writing Style as Cultural Change*

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Abstract

The late 20th century saw a transformation in professional culture around gender. We use language as a lens on cultural change, tracing how peer influence within professional networks shaped gendered pronoun choices in economic theory papers since 1970. We estimate a discrete choice model in which pronoun use reflects fixed author preferences, peer influence, and co-authorship bargaining. Peer influence plays a central and quantitatively large role in shaping writing style: when peers' use of the feminine form rises from 20% to 70%, the odds of adoption more than double. We reveal a profession of conformists: the observed shift required external cultural influence, which conformity initially suppressed but later amplified. We document a tension between individual preferences and peer influences: despite individual preferences that penalized the masculine status quo, women — who are more conformist than men — gravitated toward it by aligning with peers, especially early on. Though not initiators, their entry accelerated cultural change once under way by amplifying peer effects. Amid these opposing forces, homophily helped sustain diversity in writing styles by allowing homogeneous collaborations to express non-traditional preferences. Cultural change depends not just on who enters a profession, but on how they reshape peer dynamics once inside.

Keywords: cultural change, language, gender, social norms, co-authorships, social networks

JEL Codes: D71, D83, D85, J16, Z1

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1 Introduction

The rise in female labor force participation and the "quiet revolution" in workplace attitudes and expectations regarding gender (Goldin, 2006) transformed the second half of the 20th century. These changes extended beyond workplace policies and practices to include everyday behavior, such as linguistic choices or dating norms between coworkers. But how did such large-scale cultural change take hold and spread? While prior work has documented these broad transformations, less is known about the micro-level mechanisms that drive cultural change within professional environments. In this paper, we investigate one such mechanism: peer influence within professional networks.

We study how gender-related cultural change spreads by analyzing gendered pronoun use in academic economic theory papers from 1970 to 2019. This setting offers two advantages. First, gender typically plays no substantive role in the content, allowing authors discretion in assigning gender to abstract agents in formal models.[1] Because the content does not dictate gender, pronoun choice by economic theorists offers a unique measure of cultural expression capturing both individual beliefs and preferences (Baron, 1986) and social influences such as professional norms and expectations. Second, we construct a rich 50-year panel dataset of authors, their publications, and professional networks in a field cohesive enough for many to know each other directly, yet large enough to support indirect ties. This structure helps us identify peer influence through authors who shape others' behavior only indirectly.

The writing style of economics papers has undergone a steady transformation over the past 50 years, as shown in Figure I. In 1970, 80 percent of economic theory papers used exclusively masculine third-person pronouns (*he, him, himself*) for generic agents. By 2019, that share had dropped to 20 percent. Meanwhile, alternative pronoun forms — exclusively feminine (*she, her, herself*), exclusively plural (*they, them, themselves*), or mixed (*combining multiple forms*)[2] — emerged and spread at different times and rates. Plural and mixed forms began rising in the mid-1970s, while the feminine form gained traction around the 1990s. By 2019, masculine, feminine, and mixed forms each accounted for roughly 20 percent of published theory papers, with plural forms resurging in the 2010s.

We model the individual choices that drive the cultural change in Figure I using a discrete choice framework with three novel components. First, we allow each author's preferences to depend on two sources: an idiosyncratic component constant across all their publications

[1]For example, in principal-agent models, authors often use masculine pronouns for principals and feminine pronouns for agents. Stevenson and Zlotnick (2018) document similar patterns in economics textbooks, where gender is arbitrarily assigned to fictional characters. This contrasts with other fields where the topic often determines pronoun usage.

[2]This includes grammatical forms such as *he/she* or using different pronoun forms for different antecedents.

and a time-varying social component that reflects the behavior of their professional network. We construct this social component as the product of (i) the distribution of pronoun choices among an author's past co-authors and cited authors, and (ii) a time-invariant, author-specific coefficient that captures their responsiveness to peer behavior. Second, this peer effect coefficient can be positive or negative, allowing for *conformists*, who move toward their peers' past choices, and *contrarians*, who move away from them. Third, we model decisions in co-authored papers as the result of an implicit bargain between co-authors, with bargaining weights based on pairwise characteristics — such as differences in seniority, citation counts, or productivity — that reflect their relative influence. Coauthored papers constitute about 60 percent of our sample. By incorporating co-authorship explicitly, we avoid misattributing changes in pronoun use to an individual author when they may reflect a coauthor's preference.

A well-known debate between Martin Osborne and Ariel Rubinstein in the preface to their game theory textbook (Osborne and Rubinstein, 1994) illustrates these components and shows how co-authorship can involve compromise between opposing preferences. Rubinstein advocated for the masculine pronoun, *he*, which he considered neutral, arguing that alternatives would be distracting: "... in academic material, it is not useful to wave [language] as a flag." Osborne disagreed, describing the masculine form as having "clearly sexist origins," and promoting the use of *she* as a deliberate intervention: "I use the feminine form partly in the hope that in the future it will not be viewed as peculiar."

Estimating how professional peers influence writing style presents two empirical challenges. First, unobserved time-invariant author traits — such as ideological orientation or stylistic preferences — likely correlate with peers' behavior. Although we observe many authors multiple times, we cannot difference out these traits in our nonlinear model. Unaccounted for, these latent effects act as nuisance parameters and bias our peer influence estimates. To address this challenge, we proxy for each author's unobserved, time-invariant preference by assigning them to a latent community based on global co-authorship patterns.

Collaboration patterns in academia exhibit well-documented homophily on observable characteristics. If authors also sort on unobservable traits, then the residual structure of the co-authorship network, after accounting for observables, can reveal these latent dimensions. We formalize this idea using the stochastic block model (SBM), a canonical model in the community detection literature within network science (Karrer and Newman, 2010; Newman, 2018). SBM recovers unobserved group membership — interpreted in our setting as shared latent traits — under the assumption that link probabilities depend on group assignments. We set the number of groups to two to capture the broad, unobserved distinction between Osborne-like and Rubinstein-like orientations toward writing style. We estimate the SBM using the likelihood-based approach developed by Feng et al. (2023), and adapt it to operate over each author's acquaintance network — the set of feasible coauthors — rather than over all possible theorist pairs (see Fafchamps et al. (2010) for a related idea).

Many author pairs — due to differences in field or cohort — are not plausible collaborators. Including them would distort the estimation of the latent group structure. We construct the acquaintance network introducing a vector embedding method, *author2vec*, which adapts *word2vec* from natural language processing (Mikolov et al., 2013). Just as word2vec embeds words based on co-occurrence, author2vec embeds authors based on patterns of co-authorship and citation. We define the acquaintance set for each author as their top N $(= 5, 10, 20)$ most similar peers in the embedded academic space, based on cosine similarity. We interpret these pairs as the set of feasible collaborators.

The stochastic block model reveals strong homophily in co-authorship by ethnicity, gender, subfield, age, and citation count, but not by lifetime publication output. It partitions theorists into two communities, with the smaller group — including Martin Osborne — representing 44 percent of the sample. Osborne and Rubinstein fall into different communities, mirroring their well-known disagreement on pronoun usage. For simplicity, we refer to the smaller group as Osborne-type and the larger group as Rubinstein-type. These labels serve as illustrative proxies for contrasting approaches to writing style: a relatively more liberal (Osborne-type) and a relatively more conservative (Rubinstein-type) approach, respectively. Over time, the share of Osborne-types increased modestly from 40 percent in 1970 to 45 percent in 2019. Both communities are gender-balanced. In the model, we allow these two types to differ not only in their idiosyncratic preferences, but also in their peer responsiveness.

A second empirical challenge arises from the possibility of time-varying shocks correlated with changes in peers' writing styles. To identify peer effects, even after accounting for time-invariant author preferences, we adopt a control function approach. We estimate the control function using instrumental variables, drawing on methods from Jochmans (2023) and Johnsson and Moon (2021). Specifically, we exploit exclusion restrictions implied by the acquaintance network. We use variation in the writing style of co-authors of an author's co-authors and citees — who do not directly know the author — as instruments for peer influence. These instruments strongly predict the writing style choices of an author's direct peers.[3]

Our results show that professional peer influence plays a central and quantitatively large role in shaping writing-style choices, revealing a profession of conformists. A shift in peers'

[3] In subsubsection 4.2.2, we explain why a reduced-form IV strategy may fail to identify a well-defined treatment effect in a network setting with heterogeneous peer effects. This motivates our choice of a more structural approach.

pronoun use from 20 to 70 percent feminine more than doubles the odds that an average economist adopts the feminine form. But this peer responsiveness alone does not explain the observed aggregate pattern of change. At the aggregate level, simulations help us isolate the roles of peer effects and external cultural trends, which we also estimate in the model: in the absence of peer influence, societal trends alone would have primarily displaced the masculine form in favor of the plural, producing less stylistic diversity than we observe. Conversely, in the absence of societal change, peer effects reinforce the status quo – driving the masculine form to 85 percent by 2019. Only when both forces interact do we reproduce the observed timing and diversity of pronoun use.

Peer effects are heterogeneous: women and Osborne-type economists respond more strongly to the behavior of their peers. When the share of peers using the feminine form rises from 20 to 70 percent, the probability of adoption increases from 14 to 33 percent for a Rubinstein-type man and from 21 to 48 percent for an Osborne-type woman. Serendipitously, the latent communities reflect expected idiosyncratic preference patterns: Osborne-types place a stronger penalty on the masculine form, echoing Martin Osborne's challenge to the masculine default. Remember that we identify these communities from global patterns of co-authorship — not from writing style. The liberal Osborne-types and the women might reinforce the masculine status quo through their peer responsiveness. In a world dominated by the masculine form, their conformism pulls them toward it, working against their idiosyncratic preference.

As an implication, homophily in co-authorship does not hamper the adoption of new pronoun choices — instead, it sustains stylistic diversity. Authors with nontraditional preferences collaborate more freely with like-minded peers, enabling expression. Eliminating homophily (forcing cross-type, cross-gender coauthorship) reduces the use of feminine forms by 4 percentage points. Osborne-type women express their preferences in homogeneous teams; mixed teams dilute their influence through bargaining. Homophily can protect innovation by giving cultural minorities room to express their preferences, even as it limits exposure to difference.

Economists writing in the 1970s and 80s initiated the writing-style revolution; later cohorts largely imitated and amplified these changes. Although men initiated this shift away from masculine forms, women — especially Osborne-type women — accelerated its spread through greater peer responsiveness, enabled by homophily in coauthorship. This amplification is how the entry of women into the profession contributed to cultural change: not by shifting the share of liberal, but by strengthening the network effects that accelerated the uptake of new norms. The growing share of Osborne-types had a similar effect, suggesting that cultural change depends not just on who enters a profession, but how they reshape the dynamics of peer influence once inside. In a counterfactual where the gender and ideological composition remains frozen at 1970 levels, the share of papers using the feminine form in 2019 falls by 3 percentage points, while masculine usage rises by 4.

The main contribution of this study lies in quantifying peer effects in the diffusion of gender-related cultural change. Prior studies have documented broad shifts in gender-related behaviors, attitudes, and norms over the 20th century driven by economic, technological, and political change (Akerloff et al., 1996; Alesina et al., 2013; Goldin, 2006, 2023, 1991; Grosjean and Khattar, 2019), but less is known about the micro-level mechanisms through which these changes take hold within professional communities. We fill this gap by using language as a window into the forces shaping beliefs and behaviors related to gender equality, alongside a setting with a rich, fifty-year dataset on authors, publications, and networks. Unlike prior studies using language (Fryer and Levitt, 2004; Goldin and Shim, 2004; Lieberson and Bell, 1992), the behavior we study –pronoun choice in theoretical economics– is discretionary, and irrelevant to a paper's scientific value or publication prospects. This allows us to isolate peer influence from economic incentives or institutional constraints, providing new empirical evidence on social influence in behavioral diffusion through networks (Bikhchandani et al., 1992; Kandori, 1992; Karni and Schmeidler, 1990; Matsuyama, 1991; Young, 2014).

Our findings reveal greater conformism among more liberal economists and women, consistent with psychological evidence suggesting women are, on average, more responsive to peer behavior than men (Bond and Smith, 1996; Eagly, 1983). These groups amplified the diffusion of newer styles, but only once the broader environment began to shift. In this context, homophily played a protective role: by enabling like-minded individuals to collaborate, it allowed cultural minorities to express non-traditional preferences more freely. Rather than slowing diffusion, homophily can enable innovation to survive long enough to spread. While homophily has been widely documented across professional domains — including job search networks (Beaman, 2013; Zeltzer, 2020; Zhu, 2018), academic collaboration (Davies et al., 2022; Ductor and Prummer, 2024), and advisor-advisee relationships (Kjelsrud and Parsa, 2024) — we extend this literature by showing how it shapes the diffusion of cultural innovation. Finally, our results also relate to work on naming practices as identity signaling (Fryer and Levitt, 2004; Lieberson and Bell, 1992), and on diffusion processes involving competing norms or technologies (García-Jimeno et al., 2022; Goolsbee and Klenow, 2002; Griliches, 1957; Iyengar et al., 2011; Kelli and Gráda, 2000).

2 The economics profession in the last half century

Beyond writing styles, the economics profession has undergone major related changes in the last half-century. Two significant developments are the increasing share of female academic economists and the rising rates of academic collaboration.[4] We observe these phenomena within the network of economic theorists we study. Panel (a) in Figure II plots the share of papers with at least one female author (in blue), and the share of women publishing (in red). The share of women publishing has experienced a steady increase, from 2 percent of all authors in 1970 to 20 percent by 2020. The share of published papers with at least one female author has increased even faster, from less than half a percent in 1970 to more than 30 percent in 2020.[5] If differences in preferences between men and women are substantial, these sweeping changes in the composition of the body of authors could explain a large fraction of the observed shifts in pronoun use from Figure I. Figure A.XI plots trends in the writing-style choices of articles with female authors. Perhaps surprisingly, the writing-style choices of women have followed very similar time trends to those of men.

Trends in co-authoring also reveal momentous change. Overall, 32 percent of articles are single-authored, but the trend has been one of rapid increase in co-authoring. Panel (b) of Figure II groups authors into 10-year cohorts based on their first publication, and plots, for each year, the share of co-authored papers by economists from that cohort. While in 1970 less than half of all papers published by the 1970s cohort were co-authored, co-authoring rates among all authors are now close to 90 percent. This trend has affected all cohorts similarly, with the most senior economists showing the largest shift in co-authoring behavior. Whether co-authorship acts as a drag or as a catalyst on the diffusion of new writing styles depends on the nature of these collaborations. Increased collaboration can expose authors to others inclined to use pronoun forms they would not have chosen otherwise. If co-authorship is largely driven by ideology-based homophily, however, the potential for exposure to diverse writing preferences will be limited. Figure A.XII plots the share of articles using each writing style, separately for each 10-year cohort of authors. The trends for only-masculine, mixed, and only-feminine forms move in the same direction for all cohorts. More importantly, the level shifts across cohorts are very small. Among the earliest adopters of feminine-only and mixed styles we find Duncan Black, Gary Becker, William Baumol, Michael Spence, Thomas Roemer, Sam Bowles, Vincent Crawford and Kenneth Arrow, all members of the earliest cohort in our data. All this suggests both small cohort effects, and that innovation in writing style was led by the older cohort of authors.

The process of cultural change is not seamless. New ideas take time to develop into coherent sets of beliefs, expectations of behavior, or shared norms, and they need to compete with existing ones. Different people may hold different levels of attachment to traditional or

[4] As Giuliano and Nunn (2021) point out, variable environments are likely to induce cultural change.

[5] The share of women is lower in theoretical fields compared to applied microeconomics and other areas (Chari and Goldsmith-Pinkham, 2017; Lundberg and Stearns, 2019).

innovative beliefs and may have different psychological attitudes towards conforming to or moving away from the beliefs and behaviors of their peers.g for these sources of persistence at the author-level is necessary to identify social influences in writing styles. Indeed, the panel structure of our data lets us track individual authors over time. Panel A of Table II presents the transition matrix formed by computing the conditional probabilities of switching from using a given pronoun form to every other form, across all author-level sequences of pairs of articles. The diagonal elements are the largest, revealing some persistence. The matrix shows considerable variation in all directions, however, but also some asymmetries. For example, while only 6 percent of authors move from an only-masculine paper to an only-feminine paper, 18 percent move from an only-feminine paper to an only-masculine one.[6] To disentangle the roles of co-authorship, cohort-differences, and social influences driving these aggregate patterns we go beyond these descriptive statistics and estimate a model of writing style choice.

3 The data

In this section we describe the five key components of our data collection. The online appendix contains a more detailed description.

Selection of articles. To construct the sample of economic theory papers, we first identified the set of all papers and authors in Economics and Economics-adjacent fields from 1970 to 2020, using the metadata and full texts from two sources: *Jstor* and *Crossref*.[7] We restricted the initial sample of 710,000 published papers using a multi-step process. After cleaning non-research publications (e.g., Note from the editor, Front Matter), we excluded the articles from 35 journals specializing in econometrics, statistics, or unrelated fields such as operations research. We kept all articles from seven journals specializing in economic theory: the Journal of Economic Theory, the American Economic Journal: Microeconomics, Economic Theory, Games and Economic Behavior, International Journal of Game Theory, Games, and the Journal of Public Economic Theory. For all other published papers, we

[6]To get a sense of what the behavior reflected in this transition matrix would imply in the long run, in the first row of panel B we report the stationary distribution that would obtain in the limit under the transition matrix from panel A. Overall, the long-run distribution has around a third of only-masculine and of only-plural articles, a fifth of mixed articles, and 12 percent of only-feminine articles. These numbers are not far off what the observed distribution looked like around the mid 2000s. The remaining rows in Panel B present the implied stationary distributions that would obtain from transition matrices restricted to sequences of single-authored papers, or to the papers of authors from each of the 10-year cohorts. We report these transition matrices in Table A.XI.

[7]We obtained the *Jstor* data under a data user agreement for the project and the *Crossref* data using the defunct *Crossref* API: https://www.crossref.org/education/retrieve-metadata/rest-api/.

used their full texts to classify them as (likely) theoretical or not, using a list of microeconomics keywords and a list of econometrics keywords. We then applied a set of inclusion and exclusion criteria based on the frequencies of these keywords.

Next, we excluded articles that lacked a publication date, as well as those published before 1970 or after 2019. We also removed articles for which we could not co-reference any third-person pronouns, and articles without identifiable authors. Finally, we excluded articles with four or more authors, and papers from authors who only ever solo-authored.[8] Our final dataset contains 66,854 articles written by 29,302 unique authors. We assigned unique identifiers to each, building an author-level panel dataset using our final set of articles. Appendix subsection 11.1 contains further details.

Third-person pronouns. With then we proceed to measure our dependent variable: the gendered pronoun forms used to refer to economic agents in each paper. This requires that we distinguish third person pronoun uses that refer to model agents from uses for other reasons (e.g., to refer to a real person in the context of a citation). The growing shares of women and of co-authorship rates in the profession, in particular, make it important that we do not confound our measures of pronoun use with the increasing occurrence of references to female authors or to groups of collaborators. We tackle this problem using a *co-reference resolution* model, a natural language processing (NLP) tool used to determine the antecedents to which a particular pronoun is referring within a text. It identifies instances where different words or phrases, such as pronouns or noun phrases, point to the same person, place, thing, or concept.[9] We use *Allen NLP*, a state-of-the-art co-referencing neural network model. For each paper, we locate all occurrences of third-person pronouns and extract the surrounding text segment for each occurrence. We then apply the *Allen NLP* model to the segments to obtain the corresponding referenced noun for each pronoun.

After mapping each corresponding third-person pronoun to proper nouns in every segment, we keep only instances that refer to a noun in a keyword list of economic agents (see subsection 11.2). This list includes nouns like "individual", "worker", or "agent", to name a few. We made sure to include only gender-neutral proper nouns in this list. Figure A.XVII presents the top-50 nouns by frequency of use across all papers. For example, 6.5 percent of third-person pronouns refer to the noun "agent". While *Allen NLP* has an accuracy of at least 75 percent in standard English text, our manual checks suggest an error rate of

[8] Authors who never co-authored constitute isolated components of the network. Because in the first step of our empirical method we classify authors into two underlying types using information from co-authorship links, there is no information to classify isolated components of the network, and we must exclude them.

[9] For example, in the sentence "The consumer maximizes her utility subject to a budget constraint", a co-reference resolution model can recognize that "her" refers to the noun "consumer".

close to zero at the paper level. After having identified the relevant pronouns, we obtained the counts of masculine, feminine, and plural pronouns in each paper. The distribution of pronoun form counts across articles immediately revealed a striking pattern of mass points at 100 percent masculine, 100 percent feminine, and 100 percent plural, with the remainder of papers, those using a variety of forms, typically showing an even balance of them. This feature led us to classify the articles into four distinct groups: masculine-only, feminine-only, plural-only, and mixed if it used a combination of more than one form.

Co-authoring and citations networks. The metadata for each paper in our sample include information on its authors. Based on these data we built a time-varying co-authoring network dataset encoding as edges the cumulative number of co-authorships between every pair of authors every year between 1970 and 2019. Using *Microsoft's Academic Graph* (MAG), we did a similar exercise to build a time-varying citations network. In contrast to the co-authoring network, the citations network is directed, allowing us to distinguish between backward (i cites j) and forward (i is cited by j) citations.

Other covariates. We also build a series of covariates. First, we assign sub-fields of specialization to authors based on the *Journal of Economic Literature* (JEL) fields classification. To that end, we select a subset of theory-relevant JEL fields and retrieve generative pre-trained transformer (GPT) embeddings for the terms in each field's description.[10] For each author, we generate sentence GPT embeddings for the titles of his papers and the titles of the papers cited in his papers. We then average these embeddings to compute an author-level embedding, and compute cosine similarity distances between each author and each JEL field. Finally, we assign each author to the three sub-fields closest to him in this embedded space. Second, we classify the ethnic origin of authors using *Namsor*, a commercial software tool that identifies the likely regions of origin of names. Third, we classify the authors' sex using R's *Genderize* package, a probabilistic classifier for first names. Fourth, based on the merged MAG, *Crossref*, and JEL datasets we compute citation counts for each author by aggregating the citation counts across all of his papers.

Acquaintance network. Our full social network comprises 30 thousand economic theorists doing research on a variety of sub-fields over50 years. Differences in productive years and research areas imply that a typical theorist will only know a small subset of the social network, either personally or through their work. In practice, many pairs of individuals

[10]The Appendix reports the list of JEL fields. We retrieved embeddings from the text-embedding-ada-002 model through the *OpenAI* embeddings API. See https://openai.com/blog/new-embedding-models-and-api-updates.

whom we observe neither co-authoring nor citing each other would have never had the opportunity to interact professionally. Identifying these pairs of individuals provides us with valuable exclusion restrictions for the purpose of recovering peer effects.

We construct an underlying network of "professional interaction feasibility" that we call the *acquaintance network*. To assign acquaintance edges between pairs of economists that are sufficiently close to each other in "academic" space requires that we can measure academic distance. To do so, we exploit the global patterns of observed interaction across the profession, relying on a methodology based on another NLP tool: *word2vec* (Mikolov et al., 2013). This model is used to analyze semantic relationships between words in a corpus of text. It uses the relative frequencies with which pairs of words appear near each other (right before or after, within a few words of each other, etc.) to assign a high-dimensional vector of real numbers to each word, referred to as the word's *embedding*. The embeddings contain cardinal information about the word's meaning in relation to all other words in the corpus.[11]

Step 1: Embedding authors in academic space. We refer to our methodology as *author2vec*. In close analogy to *word2vec*, the whole set of academic articles stands for the corpus, each article stands for a sentence in the corpus, and the authors and cited economists in each paper stand for the words in a sentence. This allows us to compute the relative frequencies with which pairs of economists appear near each other across all articles. These relative frequencies then inform the estimation of author-level vector embeddings capturing the relative locations of authors in a high dimensional Euclidean academic space.[12] With the embedding vectors for each author at hand, we then compute a scalar distance measure between every pair of authors. We use the normalized dot product of the embeddings (cosine similarity), which is standard in the literature.[13] Intuitively, consider a pair of authors who has seldom cited each other, or been cited in the same articles, or shared co-authors, and whose co-authors and citees do not overlap across articles either. They will be located far from each other in the resulting embedding space, and we would like to conclude that a co-authorship between them is infeasible.

In panel (a) of Figure III we illustrate the variation in academic distance we obtain from our *author2vec* methodology. We do so honing into the local professional network of Ariel Rubinstein and Martin Osborne, who both appear as green nodes. Surrounding each of them, in yellow, are nodes representing their 10 closest economists as measured by our *author2vec* similarity metric. The larger-sized nodes among these represent co-authors. The

[11]We provide a more detailed description of *word2vec* in Appendix subsection 11.3.

[12]We set to 100 the dimension of the author embedding vectors. In *word2vev* and all other GPT models, the dimensionality of the embedding space is a model parameter. Naturally, larger corpora allow for higher dimension embeddings.

[13]Cosine similarities have support in $[-1, 1]$.

nodes in tan, in turn, represent co-authors outside of their closest 10. The length of the edges in this figure is proportional to the distance in academic space between economists, and dashed edges represent citation relationships. In addition, we labeled a select few nodes with their cosine similarity to either Osborne or Rubinstein.

Similarity predicts co-authorships and citations: one of the ten closest economists to Osborne is his co-author, and three out of the ten closest to Rubinstein are his co-authors. A large fraction of the ten closest to each are also cited by them. While co-authors of each other, Osborne and Rubinstein have a cosine similarity of only 0.12. This is not surprising: they mostly work on distinct lines of research, and there is no overlap between the sets of economists closest to them. Finally, the figure also reveals that while having fewer co-authors than Rubinstein, Osborne is on average closer to his local network than Rubinstein is. Thus, Rubinstein's professional relationships appear to be more academically diverse. The illustration reassures us that the measure of similarity we computed captures meaningful variation in academic proximity necessary to construct the acquaintance network.

Step 2: Building the Acquaintance Network. Using the academic distances from our *author2vec* methodology, we build an 'acquaintance set' $Q(i)$ for each author i. It is the set of authors with whom, we believe, i could potentially form co-authorships. Effectively, it defines an underlying network on top of which actual co-authorships may form.

We construct $Q(i)$ as follows. We build a neighborhood $L_n(j)$ for each author j, that includes the n closest authors to j based on our cosine similarity measure. We call $Y(i)$ the set of years when author i is active, which we define as the range starting 3 years before his first publication, and 5 years after his last publication. Finally, calling $A(i)$ the set of co-authors of i, including himself, we define an acquaintance set as

$$Q_n(i) = \{k : k \in L_n(j), j \in A(i), Y(k) \cap Y(i) \neq \varnothing\}.$$

The collection of these sets defines an acquaintance network. Our benchmark estimates below use $n = 10$, with alternative specifications using $n = 5$ or $n = 20$. The acquaintance sets aim to include all authors who have co-authored with author i and those who are sufficiently close in academic space to be considered potential co-authors, as long as they overlap in their active years. Indeed, average academic cosine similarity among co-authors, acquaintances, and non-acquaintances are 0.53, 0.41, and 0.03. As an illustration, consider panel (b) of Figure III, where we plot conditional densities for the cosine similarities between Ariel Rubinstein and all other economists in the professional network. The distribution of similarities with his non-acquaintances (in purple) is centered around 0, considerably to the left of the distributions with his acquaintances (in blue, red, and green), centered around

0.25. While there is a thin right tail of non-acquaintances with almost no density above 0.3, much of the density of acquaintances lies above 0.3. Rubinstein's co-authors are heavily concentrated above the 75th percentile of the acquaintance distributions, and above the 99th percentile of the non-acquaintance distribution. Indeed, three of the ten most similar authors to Rubinstein are also his co-authors (Eliaz Kfir, Michael Richter, and Yuval Salant). These patterns are typical across most economists.

Table I also illustrates a pattern of increased homophily on observables as we compare the overall sample of pairs of authors to those with an acquaintance relation, and to those who co-authored. In addition, Figure A.XIII presents the cross-scatter plots of co-authorship, forward and backward citations, and acquaintance log degree distributions. Naturally, degree in any one network is strongly predictive of degree in any other. There is, however, wide variation in the acquaintance degree at any level of co-authorship or citation counts, particularly among authors with few co-authors or with a low citation count.

4 Model of writing style

We propose a discrete-choice model of pronoun writing style. The author(s) of each paper decide among four possible styles: masculine-only, feminine-only, plural-only, or a mix of third person pronouns. We denote a generic choice by $\rho \in \{m, f, p, x\}$. It can be either a joint choice in co-authored papers or an individual choice in single-authored papers. We consider only two-person co-authorships for simplicity, but the model can readily accommodate three or more authors. An author's utility from a choice depends on an author-level, time-invariant component, which we think of as capturing latent ideology or values, and on a social interaction component capturing professional network influences. The nodes in this network change over time as new economists join the profession, and the edges change over time as new publications appear, implying new co-authorships and citations. We will allow for heterogeneity across authors in their response to the social influences. In a co-authored paper, the utility of a choice is a weighted average of the preferences of its authors.

4.1 Pronoun-choice payoffs

We denote by $a(i,j)t$ an article written by authors i and j published in year t. The notation also accommodates single-authored papers as $a(i,i)t$. The payoff from choice ρ is

$$u_{a(i,j)t}(\rho) = \alpha_\rho + \omega(\mathbf{z}_{ij})[\beta_i r_{it}^\rho + \delta_i^\rho] + (1 - \omega(\mathbf{z}_{ij}))[\beta_j r_{jt}^\rho + \delta_j^\rho] + \epsilon_{a(ij)t}^\rho, \tag{1}$$

where $\omega(\mathbf{z}_{ij}) \in [0,1]$ is a bargaining weight, and $\omega(\mathbf{0}) = 1/2$. It represents author i's weight in the joint decision, and $\mathbf{z}_{ij}$ is a vector of pairwise covariates such as their difference in cohorts, difference in citation counts, etc. The bargaining weight is the same across choices, as there is no reason why the relative influence of the authors should differ across the choices. The r_{it}^{ρ} captures the social influences from i's professional network. We consider two forms of influence over an author's time t publication: the writing styles of the full past body of work of an author's past co-authors, and the writing styles of the past papers of authors cited in the publication. We measure r_{it}^{ρ} as:

$$r_{it}^{\rho} = \frac{\sum_{k \in A_i(t)} \sum_{a \in \{a(k,\cdot)\tau, \tau < t\}} \omega_k \mathbf{1}\{\text{Paper } a \text{ uses } \rho\} + \sum_{j \in \{j \text{ cited in } a(i,\cdot)t\}} \sum_{a \in \{a(j,\cdot):\tau, \tau < t\}} \omega_j \mathbf{1}\{\text{Paper } a \text{ uses } \rho\}}{\sum_{k \in A_i(t)} \sum_{a \in \{a(k,\cdot)\tau, \tau < t\}} \omega_k + \sum_{j \in \{j \text{ cited in } a(i,\cdot)t\}} \sum_{a \in \{a(j,\cdot):\tau, \tau < t\}} \omega_j}, \tag{2}$$

where $A_i(t)$ represents the set of co-authors of author i up to time t.[14] In words, r_{it}^{ρ} is the citations-weighted share of prior papers by i's collaborators and citees that used style ρ. It varies across an author's publications as his professional network evolves over time, and across choices as a function of the previous choices of his network. It also varies across economists as each faces a different network of peers. The β_i represent peer effects. These can vary across authors but are constant across an author's publications. Because we do not restrict the support of the distribution of peer effects, the model allows for *conformist* economists, those for whom $\beta_i > 0$ and for *contrarian* economists, those for whom $\beta_i < 0$. While conformists tend to prefer choices popular among their network, contrarians tend to dislike choices popular among their network *regardless of the choice*.

We allow for this form of preference heterogeneity to vary with some author-level characteristics $\mathbf{w}_i$, modeling the underlying distribution of peer effects as drawn from a normal distribution *conditional* on $\mathbf{w}_i$:

$$\beta_i | \mathbf{w}_i \sim \mathcal{N}(\mu(\mathbf{w}_i), \sigma(\mathbf{w}_i)))$$

While a conformist follows his peers regardless of what they are choosing, a contrarian moves away from his peers regardless of what they are choosing. Recovering the distribution of peer

[14] We define the weights relative to the citation prominence of all other peers relevant for (i,t):

$$\omega_\ell = \frac{1 + \text{Citations of } \ell}{\sum_{\text{All } j,k}(1 + \text{Citations of } \ell).}$$

Alternatively we also estimate our model with uniform weights — all peers yield equal influence regardless of citation prominence — as a robustness check.

effect heterogeneity allows us to estimate the shares of conformists and contrarians in the population for each group defined by $\mathbf{w}$:

$$\mathbb{P}(\text{Conformist}|\mathbf{w}) = \int_{\beta>0} \phi(\beta|\hat{\mu}(\mathbf{w}), \hat{\sigma}(\mathbf{w}))d\beta$$

We also allow for time-invariant author-specific differences in their preference for the different writing styles, δ_i^ρ. These represent differences in values or beliefs related to the expression of gender equality in writing and are from our point of view, unobserved. The δ_i^ρ are incidental parameters. Despite the panel nature of our data, in a non-linear context like this one we cannot simply difference them out.[15] Based on our discussion on the Osborne-Rubinstein debate, we write these fixed effects as follows: some authors are ideologically similar to Rubinstein, drawing their δ_i^ρ from a distribution with mean δ_R^ρ. Some authors are ideologically similar to Osborne, drawing their δ_i^ρ from a distribution with mean δ_O^ρ. If we define O_i to be a dummy variable indicating values similar to Osborne's, we can write

$$\delta_i^\rho = \delta_R^\rho(1 - O_i) + \delta_O^\rho O_i + \xi_i^\rho, \qquad \mathbb{E}[\xi_i^\rho] = 0 \tag{3}$$

In our setting we expect the social interaction component to be dependent with these author-specific effects: $\mathbb{E}[r_{it}^\rho \delta_i^\rho] \neq 0$. If there is preferences-based homophily in peer choice, for example, previous choices of peers will be dependent with own ideology. Even in the absence of such homophily, in the presence of peer effects i's past choices, which depend on his values, may have influenced his peers' past choices.

The α_ρ are choice specific intercepts. Key to our setting, throughout we will maintain that $\mathbb{E}[r_{it}^\rho \alpha_\rho] = 0$. This is, in contrast to much of the empirical literature estimating discrete choice models, ours is a setting without unobserved choice-specific fixed effects that may be dependent with the endogenous regressor of interest. For example, in models of residential location choice (Bayer and Timmins, 2007) or of differentiated product demand (Nevo, 2003), choice-specific payoffs depend on choice-specific unobserved attributes that make a choice more or less valuable to everybody (e.g., access to public transportation in the case of neighborhoods, sweetness in the case of cereals, etc.). The gender choice of third-person pronouns is one where unobserved attributes are absent because the value of a given choice

[15] A common approach in discrete choice settings following Chamberlain (1980) is to write down a likelihood that conditions on a sufficient statistic for the incidental parameters. This sufficient statistic turns out to be the vector of total counts of realized choices across all observations for a given unit. In our setting such an approach has two disadvantages. First, two thirds of the articles are co-authored, so the choice-specific payoffs depend on two different nuisance parameters. Second, a conditional likelihood approach does not allow recovering the the author-specific effects, which would restrict our ability to decompose the evolution of writing style norms into the contributions of peer influence, underlying values, and co-authorship.

is purely social, this is, it depends only on how much others value it and the signaling concerns around this. The scientific contribution of an economic theory paper is invariant to the choice of gendered pronouns it uses.[16]

Finally, the $\epsilon^{\rho}_{a(i,j)t} = \varphi^{\rho}_{t} + \widetilde{\epsilon}^{\rho}_{a(i,j)t}$ represent time-varying unobservables. On one hand, φ^{ρ}_{t} may represent overall societal trends in relative popularity of writing style ρ coming from outside the economic theorist network. We will account for them with time fixed effects. On the other hand, $\widetilde{\epsilon}^{\rho}_{a(i,j)t}$ may represent idiosyncratic shocks affecting the authors of paper $a(i,j)t$, possibly dependent with $(r^{\rho}_{it}, r^{\rho}_{jt})$: $\mathbb{E}[(r^{\rho}_{it}, r^{\rho}_{jt})\widetilde{\epsilon}^{\rho}_{a(i,j)t}] \neq \mathbf{0}$. For example, autocorrelation in the $\widetilde{\epsilon}^{\rho}_{a(i,j)t}$'s will generate dependence with the social influences, r^{ρ}_{it}, through network effects: i's past shock induces him to choose a particular writing style; his conformist peers will subsequently mimic his choice; their choices now influence author i at time t.

Even if in the population the distribution of peer effects is stationary, the composition of the pool of economists may have changed ideologically, and definitely has seen an increasing share of women. Thus, we allow $\mathbf{w}_i$, the characteristics governing the distribution of peer effects, to include O_i and sex, as it may be that men and women or conservatives and liberals differ on the extent of heterogeneity and on the average strength of their peer effects. Finally, only-plural will be the baseline category for estimation.

To estimate the discrete choice model based on the preferences in (1) we must address two main econometric challenges. First, idiosyncratic time-varying unobservables, $\widetilde{\epsilon}^{\rho}_{a(i,j)t}$, may be dependent with social influences through the network structure. Second, ideological preferences, O_i, are unobserved and may also be dependent with social influences. We now address the first concern, and turn to the second concern in section 5.

4.2 Identification: leveraging the acquaintance network

The acquaintance network we described in section 3 will provide us with the exclusion restrictions to address the empirical challenges highlighted above.

[16]An argument could be made that the use of some pronoun forms can improve the readability or the quality of the writing in a paper, implying differences in the fundamental value of the different choices. For example, giving different genders to different players in a model — the mixed choice– may allow the reader to more easily identify who the author is referring to. The recent rise in popularity of the feminine-only and the plural-only forms suggest many authors do not share this view. Moreover, some may argue that this added flexibility could easily make writers less careful in constructing their sentences, and may thus hurt the writing quality itself. Thus, we believe that any differences in scientific writing quality directly coming from using one type of pronoun form over another are at most second order. Another possibility is that differences in the fundamental value of using different pronoun forms emerge from editorial practices that condition the likelihood of publication of a paper on the pronoun form used in it. We are unaware of such behaviors in the Economics profession. Even if editors do no condition their publication decisions on pronoun choice, this could still be a concern if an author holds the belief that they do. We empirically test this possibility below.

4.2.1 Control function

We first address the dependence between social influences and time-varying unobservables. We do so with a control function approach following ideas in Jochmans (2023) and Johnsson and Moon (2021), and exploiting our acquaintance network. Specifically, we build time-varying instruments for r_{it}^{ρ}. The logic of these instruments is as follow: if an author i has peers (past co-authors and citees) who are themselves subject to peer influences, then the pronoun choices of the peers of these peers will generate variation in their pronoun choices, this is, in r_{it}^{ρ}. The choices of past peers of an authors' peers are thus relevant. If we can find peers of i's peers who are *not* in i's acquaintance set, then we know they do not directly influence his writing style. The choices of non-acquaintance peers of i's peers are thus excludable. We construct such instruments as

$$z_{it}^{\rho} = \frac{\sum\limits_{k \in A_i(t) \cup C_i(t)} \sum\limits_{P_i(k,t)} \omega_k \mathbf{1}\{\text{Paper } a(\ell, m)\tau \text{ uses } \rho\}}{\sum\limits_{k \in A_i(t) \cup C_i(t)} \sum\limits_{P_i(k,t)} \omega_k}, \tag{4}$$

where $C_i(t)$ is the set of i's citees up to time t, and $P_i(k,t) = \{a(\ell, m)\tau : \tau < t \text{ and } \ell \in A_k(t) \cap Q_i^C \cap C_i(t)^C, m \in Q_i^C \cap C_i(t)^C\}$ denotes the set of articles by authors who are not acquaintances of author i and have not been cited by author i, but who are past co-authors of one of his past co-authors or citees, k.[17] Because ours is a panel data setting, we use variation over time in the indirect exposure to non-acquaintances of peers' writing-style choices. With this purpose in mind, we compute first-difference versions of (4), $\Delta z_{it}^{\rho} \equiv z_{it}^{\rho} - z_{it-1}^{\rho}$, where the difference is between two consecutive papers published by author i.

To understand the variation in Δz_{it}^{ρ}, consider Figure IV. In it, we represent the professional network of Debraj Ray across two publishing years: 1993 on the left and 1994 on the right. Green circles represent his acquaintances, and the name labels represent people he had co-authored with previously. Pink circles represent the co-authors of Ray's co-authors who are not in his acquaintance set. For example, in 1993 Douglas Bernheim had 4 co-authors who were themselves outside Ray's acquaintance set. Between 1993 and 1994, Ray developed several new co-authorship relationships, one of them with Kalyan Chatterjee. Chatterjee had himself three past co-authors who were not Ray's acquaintances. Thus, the past writing style choices of these three people generate the variation in the instrument for Ray in 1994. Figure A.XV provides a similar example, this time looking at Drew Fudenberg's professional

[17] If the set $\bigcup\limits_{k \in A_i(t) \cup C_i(t)} P_i(k,t)$ is empty, this is, if for a given author-publication period none of his co-authors or citees have co-authors that are not his acquaintances, we define $z_{it}^{\rho} = 1/4$ for all $= \rho$, the maximum entropy multinomial distribution among four choices.

network. Between 1992 and 1993 he developed a new co-authorship relation with Christopher Harris, and Harris had himself three past co-authors not in Fudenberg's acquaintance set.[18]

Because the social interaction variables r_{it}^{ρ} in (1) are fractions that add up to 1 across ρ, we implement our control function approach by estimating a fractional response multinomial logit reduced form regression (Mullahy, 2011), under which:

$$\mathbb{E}[r_{it}^{\rho}|\Delta\mathbf{z}_{it}] = \frac{\exp(\Delta\mathbf{z}_{it}'\boldsymbol{\pi}^{\rho})}{1 + \sum_{\rho\in\{m,f,x\}} \exp(\Delta\mathbf{z}_{it}'\boldsymbol{\pi}^{\rho})}, \tag{5}$$

where $\Delta\mathbf{z}_{it} = (\Delta z_{it}^{m}, \Delta z_{it}^{f}, \Delta z_{it}^{x})$. These conditional mean functions capture the part of the variation in i's peers' writing-style choices induced by time-series variation in the choices of their peers who are themselves non directly connected to i. Under the identifying assumption that $\mathbb{E}[\Delta z_{it}^{\rho}\widetilde{\epsilon}_{a(i,j)t}] = 0$, the residuals from the fractional response model, $\eta_{it}^{\rho} = r_{it}^{\rho} - \widehat{\mathbb{E}}[r_{it}^{\rho}|\Delta\mathbf{z}_{it}]$, contain the endogenous variation in r_{it}^{ρ} which we include as a regressor in (1). Notice that in co-authored papers, we need to include both η_{it}^{ρ} and η_{jt}^{ρ}.[19]

Table III reports our estimates of the the $\boldsymbol{\pi}^{\rho}$ coefficients from (5). Throughout, the baseline category is only-plural. The top panel reports our benchmark results, where we consider co-authorships and citations as generating edges in the professional network. The columns report results for the share of only-masculine, only-feminine, and mixed papers among an author's peers. Relative to the only-plural share, the coefficients reveal a consistent pattern: an increase in the share of masculine or feminine form use by non-acquaintance co-authors of peers increases the likelihood of the corresponding choice by the peers more than the alternatives. An increase in the share of the mixed form by non-acquaintance co-authors of peers reduces the likelihood of the masculine form choice by peers. The middle and bottom panels explore the robustness of these results to restricting the professional network to only co-authorships, or only citations. In both cases the pattern of results is very similar, with somewhat larger coefficients when restricting attention to the citations network.

Estimates from fractional logit models are known to be hard to interpret directly. In Table IV, thus, we explore the robustness of these result in relation to functional form,

[18] Jochmans (2023) proposes a similar approach, in the context of endogenous selection of peers. There, link decisions that involve a given individual do not need to be independent of one another, but they are independent of link decisions made by other pairs of individuals located sufficiently far away in the network. This is different from the popular IV strategy from Bramoulle et al. (2009) which uses covariates from second-degree neighbors as instruments in a cross-sectional setting, and does not require the absence of alternative paths between those second-degree neighbors and a given node. Because we have access to panel data, we can use past choices instead.

[19] Johnsson and Moon (2021) also propose using a control function to recover peer effects, but do so in a cross-sectional network setting with endogenous network links instead.

presenting linear regression estimates separately for each pronoun form share. Instead of using the first difference of the instruments as regressors, we use their levels from (4), and include author-level fixed effects to exploit only within-author variation. The results are consistent with those from Table III: the instrument for the corresponding pronoun form always positively and significantly predicts the peer's pronoun form share. Just as before, we present results for networks that include both co-authors and citees in the top panel, only co-authors in the middle panel, and only citees in the bottom panel.

4.2.2 Discussion: what about linear IV?

The availability of instruments for the endogenous pronoun form choices of peers we just described may raise the following question: why not estimate a linear two-way author-fixed effects model where the dependent variable is a dummy for a given pronoun form choice, and we instrument the peers' average choices with the same instruments we use to estimate the control function outlined above? Such an IV estimator would not in general identify any well defined causal effect in a setting like ours. This is because in a network setting with heterogeneous peer effects, the standard monotonicity requirement for the first stage may not hold. In the treatment effects literature, for example, it is well know that IV in general does not recover a treatment effect for any sub-population in the presence of defiers (Angrist et al., 1996; Dahl et al., 2023).

In our setting, we have argued that apriori there can be conformist and contrarian economists. Consider an author i, conformist or contrarian, with one peer, j. If j is a conformist, he will be more likely to choose a particular writing style when that style is more popular among his peers, k. Author i is thus a *complier*, since his treatment variable, j's choice, is increasing in k's choice. If j is a contrarian, however, he will be more likely to choose a particular writing style when that style is less popular among his peers, k. Author i is thus a *defier*, since his treatment variable, j's choice, is decreasing in k's choice.

5 Co-authorship formation model

In this section we turn to addressing the second econometric challenge we raised in subsection 4.1, namely the presence of unobserved time-invariant preferences related to author's values or beliefs, possibly dependent with the social influences they experience. Our starting point is the ample empirical evidence of homophily in academic collaboration networks. Numerous studies have explored this question in the context of the Economics profession. Besancenot et al. (2017); Ductor et al. (2023); Ductor and Prummer (2023); Freeman and

Huang (2014); Önder et al. (2021), for example, show there is strong homophily in co-authorship along the gender, ethnicity, fields of specialization, and productivity dimensions. Fafchamps et al. (2010) argue, in addition, that social distance between economists also drives co-authorships. In work studying other scientific fields, Combes and Givord (2018) also find strong gender homophily in co-authorships, and Newman (2001) finds that network distance (what he refers to as 'small worlds') is also a driver of collaborations.[20]

If there is homophily in co-authorships along the unobserved preferences reflected in δ_i^ρ, we would expect clustering of edges: a high prevalence of co-authorship between pairs of authors with relatively more conservative (or traditional) preferences ($O_i = 0$) and between pairs of authors with relatively more liberal (or innovative) preferences ($O_i = 1$), compared to pairs of authors with dissimilar ones. Our key observation is that observed patterns of co-authorship across the whole network of economic theorists will contain information about ideological similarity. Consider, for example, a setting where there is homophily in collaborations based on an observed and an unobserved dimension. Suppose two authors in this network are very dissimilar in the observed characteristic but are, nevertheless, seen co-authoring. We may infer they are similar in their unobserved characteristic. Conversely, suppose two authors are very similar in their observed characteristic but are not seen coauthoring. We may infer they are dissimilar in their unobserved dimension.

5.1 The community detection problem

Based on the observation above, we estimate a simple homophily-based model of co-authorship borrowing ideas from the Network Science literature.[21] This literature has studied extensively the problem of detecting unobserved types within a network. It refers to it as the *community detection* problem (Karrer and Newman, 2010; Newman, 2001, 2018). This will allow us to classify all authors in the network into two groups, or communities. One which we interpret as having preferences more similar to those expressed by Rubinstein, and one with preferences more similar to those expressed by Osborne. Thus, we will be able to recover an

[20]Recent work has also explored potential reasons for the observed homophily along gender lines, including preferences over risk (Lindenlaub and Prummer, 2020), gender-based asymmetries in recognition for collaborative work (Sarsons et al., 2021), and signaling concerns (Onucich and Ray, 2021). Related work has shown that the extent of co-authorship has increased substantially in the last half a century (Anderson and Richards-Shubik, 2022; Hammermesh, 2013; Kuld and O'Hagan, 2018; McDowell and Melvin, 1983), that the average age of authors has been increasing (Hammermesh, 2015), and that the Economics profession shows "small world" patterns because a small number of star authors co-author widely with other authors who themselves have few co-authors (Goyal et al., 2006).

[21]In Economics, several papers have proposed approaches to estimate models of network formation with unobserved drivers of link formation. In some instances these models bypass estimating the unobserved effects (Fafchamps et al., 2010; Graham, 2017). In others, they exploit additional structure (dePaula et al., 2018; Islam et al., 2022).

estimate of O_i for all authors.[22]

The workhorse inference-based model for community detection is called the Stochastic Block Model (SBM). Here we implement a covariates-adjusted SBM following Feng et al. (2023), to allow for homophily in other observable characteristics. The SBM presumes the existence of a finite number of communities, which we will fix to two, takes a set of nodes —authors in our setting — and models the number of links between every pair of them as draws from a Poisson distribution that depends on pairwise characteristics. Such a model is ideally suited to settings where the network is sparse, and where there can be more than one edge between a pair of nodes. Both of these are features of co-authoring network: the number of co-authorships is very small compared to the number of all potential co-authorships, and some pairs of authors share more than one publication.[23]

We modify the workhorse SBM model in one key way: whereas the standard model allows for edges to form between every pair of nodes, we restrict co-authorships to arise only among pairs of authors who are in each others' acquaintance sets. This is for two reasons. First, an econometric challenge that arises in models estimating dyad-level equations is the quadratic explosion of potential edges as the the number of nodes grows, introducing computational difficulties. Second and more importantly, in relatively large social networks a large (and increasing in network size) share of potential edges are infeasible because most individuals, in practice, can only form relationships with a local subset of others. Considering dyads who could not possibly have formed a connection will lead to bias in the estimates of the strength of homophily. Suppose, for example, that shared ethnicity does increase the likelihood of link-formation, but that only geographically close people are feasible candidates for collaboration. If pairs of people who would never face the opportunity of collaborating share, for example, the same ethnicity, a model that uses the information from these pairs of people will under-estimate, possibly severely, the importance of ethnic similarity. Because we constructed the acquaintance network precisely to capture subsets of authors who are likely to be near each other in the professional sphere, restricting the possible co-authorships to happen only between mutual acquaintances allows us to address this issue. The acquaintance network is, thus, an underlying set of edges on top of which co-authorships can be formed.

[22] The SBM relies on the global patterns of co-authorship to infer the community memberships. Because authors who never co-authored are isolated individual components of the overall graph, there is no information to classify them into either community. Thus, we must exclude them from our estimating sample. 11 percent of authors in our original network never co-authored, of whom 87 percent only published one paper.

[23] Another convenient feature of the SBM in our setting is that it allows us to abstract away from the time dimension of the co-authoring problem: it models the intensive margin of co-authorship. Because our interest is to learn a time-invariant feature of the set of authors, the approach is not very restrictive while allowing us to avoid modelling the complex dynamics of co-authoring decisions over time.

5.2 The acquaintance network-adjusted SBM

Each of the n economic theorists has an unobserved (to us) type $\tau_i \in \{\ell, c\}$. These two types differ in their ideological preferences. The fraction of ℓ types in the population is π_ℓ, and the fraction of c types is $\pi_c = 1 - \pi_\ell$. Conditional on types, the number of co-authorships between $i \in Q(j)$ and $j \in Q(i)$ is Poisson distributed:

$$a_{ij} \sim \mathcal{P}(\omega_{\tau_i \tau_j} e^{\mathbf{x}'_{ij}\boldsymbol{\gamma}}), \qquad \Omega = \begin{pmatrix} \omega_{\ell\ell} & \omega_{\ell c} \\ \omega_{\ell c} & \omega_{cc} \end{pmatrix}$$

where $\boldsymbol{\tau} = (\tau_1, \tau_2, ..., \tau_n)$ is the vector of true types, and Ω governs the degree of type-based homophily in the network formation technology.[24] Diagonal entries that are larger in magnitude than the off-diagonal entries reflect homophily. We do not impose such a constraint in estimation. To allow for homophily along observables, we include the following pairwise covariates in $\mathbf{x}_{ij}$: dummies for same ethnicity and same gender, a count variable for the number of common sub-fields, the author's age difference, the author's log citations difference, the author's log productivity difference, and the log of the product of the author's productivities[25].

The joint likelihood of observing co-authoring matrix $\mathbf{A}$ and an assignment of types $\boldsymbol{\tau}$ is

$$\begin{aligned} \mathcal{L}(\mathbf{A}, \boldsymbol{\tau} | \Omega, \boldsymbol{\gamma}, \pi, \mathbf{X}) &= \mathbb{P}(\mathbf{A} | \boldsymbol{\tau}, \Omega, \boldsymbol{\gamma}, \pi, \mathbf{X}) \mathbb{P}(\boldsymbol{\tau} | \Omega, \boldsymbol{\gamma}, \pi, \mathbf{X}) \\ &\propto \prod_{i=1}^{n} \left[\prod_{j \in Q(i)} \left(\omega_{\tau_i \tau_j} e^{\mathbf{x}'_{ij}\boldsymbol{\gamma}} \right)^{a_{ij}} \exp(-\omega_{\tau_i \tau_j} e^{\mathbf{x}'_{ij}\boldsymbol{\gamma}}) \right] \pi_{\tau_i}. \end{aligned} \tag{6}$$

Solving the community detection problem entails maximizing this likelihood jointly over the type shares, π_ℓ, the homophily coefficients $\boldsymbol{\gamma}$ and Ω, and the assignment vector $\boldsymbol{\tau}$. In Appendix subsection 11.6 we provide the details of the procedure, which closely follows Feng et al. (2023). It entails noticing that the maximum likelihood estimates for π_ℓ and Ω have closed forms as functions of $\boldsymbol{\tau}$ and $\boldsymbol{\gamma}$ only, so we can compute a profile likelihood that is only a function of $\boldsymbol{\tau}$, and $\boldsymbol{\gamma}$. In turn this profile likelihood can be optimized in two steps. First, finding the optimum over $\boldsymbol{\gamma}$ for a fixed $\boldsymbol{\tau}$. Then, optimizing over $\boldsymbol{\tau}$ using an EM algorithm.

[24] The model accommodates single-authored papers in the form of 'self-edges'.

[25] Newman (2018) shows that including this last covariate is akin to a SBM with 'degree-correction', this is, it accommodates networks with high dispersion of its degree distribution.

5.3 Estimation results form the co-authoring model

Table V presents our estimates. The first column reports our benchmark results, under the acquaintance set definition based on the ten closest economists as we described in section 3. The second and third columns report results under tighter (five closest) and looser (twenty closest) alternative acquaintance set definitions. The top block reports estimates for $\boldsymbol{\gamma}$. Except for the difference in lifetime productivities between the pair of authors, all other pairwise covariates are strong predictors of co-authorship. Pairs of economists of the same ethnic background, same sex, and sharing sub-fields in common are more likely to write together. Larger age gaps and larger citations gaps decrease the likelihood of co-authoring. The point estimates on all these pairwise covariates are very precisely estimated, confirming strong homophily in academic collaboration within the economic theory field.

The bottom block reports the estimates for implied homophily along the unobserved type dimension, Ω. These parameters are informed by the relative frequencies of observed co-authorships given the optimal community assignment $\boldsymbol{\tau}$. They reveal, for example, that conditional on observables, average co-authorships are nine times higher between ℓ types than between an ℓ and a c type, and three times higher between c types than between an ℓ and a c type. These parameters are also very precisely estimated.

Turning to the community assignment $\boldsymbol{\tau}$, we classify 56 percent of authors in one group, and 44 percent in the other. In the absence of external information the assignment cannot tell us what each group represents, which is the standard label switching issue. In our context however, we do have additional information. Across all specifications, we always find Martin Osborne and Ariel Rubinstein assigned to different communities. As a result, we refer to the two groups as the (relatively more innovative) Osborne type, and the (relatively more traditionalist) Rubinstein type. The Rubinstein group is the largest of the two. Indeed, across the two alternative specifications in the table, 85 and 82 percent of authors are consistently classified into the same group as they are in the benchmark specification.

While we find relatively balanced group sizes, the growth in the profession since the 70s and the rising share of women in it could imply large differences across cohorts in the relative sizes of both groups. Because the community detection approach allows us to classify every author into one of the two groups and we observe the first publication of each of them, we can plot the type distribution across cohorts. Figure V does just that, plotting for each 5-year cohort of authors, the share assigned to the Osborne group under our benchmark specification. We find the Osborne group share to be stable around 39 percent for the 70s to 80s cohorts. The Osborne share grows with the 90s cohorts to around 46 percent, and stabilizes at around that number among the subsequent cohorts. Thus, although there is some compositional change over time towards the more liberal type, it is relatively modest and certainly insufficient to account for the large changes in writing styles observed over the same period. The community assignment also allows us to compare both groups in terms of their observables. Figure A.XIV plots the distributions of the main author-level characteristics we observe conditional on type. Across the board, both communities look very similar in their sex, ethnicity, and fields compositions, and have very similar productivity and citations distributions. Our results in the next section confirm that Osborne-type authors are more likely to choose mixed forms and less likely to choose masculine forms.

The reader may notice that we did not include a pairwise covariate capturing shared institutional affiliations. This is because we were unable to collect that information systematically across all authors in the network. A concern may be, thus, that the community assignment we estimated is mostly capturing shared institution-based homophily. To assuage this concern, we collected detailed institutional affiliation information for the subset of professors from the top-ranked 39 Economics programs, starting in 1990. For this sub-sample of authors we explored whether university affiliations predict community membership. We do so by running linear regressions of the 'Osborne-group' dummy variable on a dummy variable capturing affiliation, separately for each institution. Figure VI presents a scatter plot of the coefficient on the university dummy against its corresponding p-value across all 39 regressions. Only 3 of them yield statistically significant coefficients at the 5 percent level, and 34 of them are smaller than 0.1 in magnitude. At least among this elite set of economic theorists, university affiliation does not predict the community assignment.

6 Estimation of the writing-style model

6.1 Estimation

Armed with our community assignment from subsection 5.3, we set $O_i = 1$ for all authors classified in Osborne's community. Together with the control function estimates from subsection 4.2, we can write $u^{\rho}_{a(ij)t}$ from (1) as $u_{a(ij)t} = V^{\rho}_{a(ij)t} + \nu_{a(ij)t}$, where $V^{\rho}_{a(ij)t}(\beta_i, \beta_j) \equiv$

$$\widetilde{\alpha}^{\rho} + \varphi^{\rho}_t + \omega(\mathbf{z}_{ij})[\beta_i r^{\rho}_{it} + \delta^{\rho} O_i] + (1 - \omega(\mathbf{z}_{ij}))[\beta_j r^{\rho}_{jt} + \delta^{\rho} O_j] + \lambda^{\rho}[\hat{\eta}^{\rho}_{it} + \hat{\eta}^{\rho}_{jt}], \tag{7}$$

$\widetilde{\alpha}^{\rho} \equiv \alpha^{\rho} + \delta^{\rho}_R$, $\delta^{\rho} \equiv \delta^{\rho}_O - \delta^{\rho}_R$, and $\nu_{a(ij)t}$ are independent of $(r^{\rho}_{it}, r^{\rho}_{jt}, O_i, O_j)$ given $(\hat{\eta}^{\rho}_{it}, \hat{\eta}^{\rho}_{jt})$ and type-1 extreme value distributed. As a functional form for the bargaining weights we use

$$\omega(\mathbf{z}_{ij}) = \frac{1}{1 + \exp\left(-\boldsymbol{\kappa}' \mathbf{z}_{ij}\right)}$$

Under (7), and collecting in vector $\boldsymbol{\theta}$ all parameters, the unconditional likelihood of observing writing style $p_{a(ij)t} = \rho$ for paper $a(ij)t$ averages over the distribution of peer effects for each author conditional on their vector of characteristics $\mathbf{w}_i$:

$$\mathbb{P}(p_{a(ij)t} = \rho | \mathbf{w}_i, \mathbf{w}_j, \mathbf{z}_{ij}; \boldsymbol{\theta}) = \int\int \frac{\exp\left(V^{\rho}_{a(ij)t}(\beta_i, \beta_j)\right)}{1 + \sum_{s\in\{m,f,x\}} \exp\left(V^{s}_{a(ij)t}(\beta_i, \beta_j)\right)} d\Phi(\beta_i|\mathbf{w}_i) d\Phi(\beta_j|\mathbf{w}_j).$$

We think of the distribution of peer-effect heterogeneity as capturing traits that are possibly stationary in the overall population. Over the last fifty years, however, the Economics profession has grown in size. For example, while we see 1,620 economists from the 1970s cohort, we see 4,970 from the 1990s cohort, and 11,317 from the 2010 cohort. The profession also has shifted its sex composition towards women. Because the new entrants or women as a whole could differ in their preferences relative to incumbents, we allow $\mathbf{w}_i = (\text{woman}_i, O_i)$ to include the authors' sex and community assignment dummies.

The likelihood for the writing style choices across all articles is thus

$$L(\boldsymbol{\theta}|\mathbf{P}, \mathbf{W}, \mathbf{Z}) = \prod_{a} \prod_{\rho\in\{m,f,x,p\}} \mathbb{P}(p_{a(ij)t} = \rho|\mathbf{w}_i, \mathbf{w}_j, \mathbf{z}_{ij})^{\mathbf{1}\{p_{a(ij)t}=\rho\}}. \tag{8}$$

We use maximum simulated likelihood to estimate $\boldsymbol{\theta}$.[26] The vector of parameters includes the three pronoun specific intercepts $\widetilde{\alpha}^{\rho}$, the three sets of time effects φ^{ρ}_{t} (in practice we include time effects for groups of 5 years with the exception of 1970-1974 and 1975-1979 for which we include a single time effect[27]), the three coefficients δ^{ρ} on the Osborne community dummy, the three coefficients λ^{ρ} on the control function, five coefficients on the pairwise covariates $\boldsymbol{\kappa}$ on the bargaining weight function, and six coefficients governing the distribution of peer effect heterogeneity[28]: $\mu_{\mathbf{w}}$, $\sigma_{\mathbf{w}}$.

6.2 Results

Our main results for the writing-style choice model use the $n = 10$ acquaintance sets definition, and consider both past co-authoring and citation relations as channels of peer influence. Figure VII presents the point estimates and confidence intervals for the time effects, φ^{ρ}_{t}. These capture societal changes in the overall popularity of the different writing styles, external to the profession, influencing the economists writing at the time. The estimates re-

[26]See Appendix subsection 11.7 for additional details about the estimator.

[27]In 1970-1974 no papers used the only feminine choice, so the time effects for that group of years would be unidentified.

[28]Because the number of women in the profession is small, in practice we do not estimate separate variances for men and women.

veal two main features: substantial differences over time in the relative preference for writing styles, and a secular fall in the dispersion of those preferences. For example, among articles written in 1970-1979, the likelihood ratios for choosing the masculine form over the feminine, mixed, and plural forms were 440 to 1, 22 to 1, and 1.1 to 1. The most recent articles, in contrast, show no preference between the masculine, feminine, and mixed forms. They do show a preference for the plural form over them, with a likelihood ratio of 2.7 to 1.[29]

Table VI presents estimates and standard errors for the remaining parameters. The pattern of estimates on δ^ρ reveals that relative to the plural form, authors in the Osborne community are less likely to choose the masculine form (-0.36, s.e.$=$ 0.04), as likely to chose the feminine form (-0.02, s.e.$=$ 0.13), and more likely to chose the mixed form (0.88, s.e.$=$ 0.07). This pattern confirms that the subset of authors we identified as being part of Osborne's community does share affinity with his values related to the expression of views on gender in their writing. Moreover, it confirms that this otherwise unobserved dimension of preferences driving homophily in co-authoring is indeed related to relatively more or less traditional views.

The coefficients on the control function regressor, λ^ρ, statistically significant across all three writing styles, corroborate the importance of controlling for the endogeous component of the variation in peer influences. Turning to the co-authoring bargaining weights θ, we find that larger age gaps favor the preferences of the older co-author. In contrast larger citations and productivity gaps tend to favor the preferences of the less cited and less productive author (conditional on their age difference). Sex and ethnicity differences do not alter the relative weights of the co-authors.

We now turn our focus to the peer effects' findings. While panel b of Table VI reports means and standard deviations for the estimated normal distributions of peer effect heterogeneity across the four groups defined by community and sex, Figure VIII presents the implied densities. Across all groups, the mean peer effects are very precisely estimated, and reveal several key features: First, the estimates comfortably rule out the presence of contrarian economists in the profession. For all groups, the peer effect distributions only assign positive mass to positive values of β_i. Second, we find only a moderate amount of heterogeneity in peer effects. This is particularly the case among Rubinstein-community economists, for which 95 percent of their implied β_i's are between 1.5 and 1.6. Third, we find larger average peer effects for women than for men, particularly among Osborne community economists. The mean peer effect for Osborne-community women, 1.92, is statistically larger than the mean effects for all other groups. These findings suggest an overwhelmingly

[29]For the oldest articles, $\exp(0.1)/\exp(-6) = 440$, $\exp(0.1)/\exp(-3) = 2$, $\exp(0.1)/\exp(0) = 1.1$. For the most recent articles, $\exp(0)/\exp(-1) = 2.7$.

conformist profession, and stronger responses to peer influence by liberal economists.

To assess the quantitative implications of our estimated peer effects, consider an average Rubisntein-community male economist who experiences his peer's choices changing from 80 percent masculine style-20 percent feminine style, to 30 percent masculine style-70 percent feminine style. This would make him 46 percent less likely to choose the masculine, and correspondingly, 2.15 times more likely to choose the feminine form for his next publication. Under the same experiment, an average Osborne-community female economist would be 38 percent less likely to choose the masculine, and correspondingly, 2.6 times more likely to choose the feminine form for her next publication.[30] An implication of these estimates is that the growth of the relatively more liberal group (see Figure V), and the increasing participation of women (see Figure II) in the profession have increased the aggregate strength of peer influences over time.

6.2.1 Model fit

Panel a of Figure IX plots the aggregate distribution of writing style choices over time from a simulation of our model using the estimated parameters. We do this taking the set of articles and the professional network relations fixed, simulating pronoun form choices for each paper, and computing the resulting peer influence variables r^{ρ}_{it} for each year that then determine choices for subsequent articles. We take the average 1970-1974 observed distribution of choices as an initial condition for this simulation. A comparison of Figure I and panel a of Figure IX illustrate that our model does a remarkable job at fitting the time trends and levels of the distribution of writing styles, and the relative popularity of each over time. Perhaps the only discrepancy to note is that our model predicts a somewhat earlier lift-off in the popularity of the mixed form compared to its more gradual take-off in the data.

6.2.2 Peer influence, women, co-authorship, cohorts, and external trends.

What do the estimates of our model teach us about the contributions of societal influences, peer effects, the entry of women and new cohorts into the profession, and co-authoring as drivers of the change in writing norms over the last fifty years? We answer this question simulating the evolution of writing styles under alternative scenarios using our estimates and the same methodology we described in subsubsection 6.2.1. Each of these exercises allow us to quantify the effects of a given margin of interest. We first discuss peer influences and then compositional changes.

[30] For the male economist, $\exp(1.54 \times 0.3)/\exp(1.54 \times 0.8) = 0.46$, and $\exp(1.54 \times 0.7)/\exp(1.54 \times 0.2) = 2.15$. For the female economist, $\exp(1.92 \times 0.3)/\exp(1.92 \times 0.8) = 0.38$, and $\exp(1.92 \times 0.7)/\exp(1.92 \times 0.2) = 2.6$.

Quantifying the role of peer influences. To quantify the importance of social interactions in steering the evolution of writing norms, we begin with an exercise that fixes the time effects, φ_t^ρ, to their 1970 level throughout, effectively shutting off the societal trends we recovered (see Figure VII). Panel b in Figure IX presents the aggregate dynamics of pronoun form choice in this scenario. When compared to the baseline simulation in panel a, it reveals the first-order importance of these external trends; in their absence, the profession would not have abandoned the masculine form as its overwhelming favorite, and the mixed and feminine forms would not have taken off. Moreover, the positive peer effects reinforce the early asymmetry in choices, making the masculine form share grow from 65 to 80 percent, and the plural form share shrink from 33 to 18 percent between 1970 and 2019. The last column of Table VII summarizes this comparison reporting the percentage point difference between the 2019 distribution of choices in this scenario and the baseline simulation.

While the profession's conformity would lock-in and exacerbate the 1970's behaviors in the absence of external trends, it steers norm evolution in a different direction in their presence. We illustrate this in panel c of Figure IX. It presents the evolution of writing-style choices in a scenario where, rather than shutting off the external trends, we shut off the peer effects by setting $\beta_i = 0$ for all economists. In the absence of peer influences, the share of papers using the plural form is 10 percentage points higher than in the baseline simulation during the 70s and 80s compared to the baseline (panel a). It also grows faster, reaching 55 percent of all papers by the late 80s. This is at the expense of the masculine form, and illustrates that the immense popularity of the masculine from in the early part of our period of study was to a large extent sustained by peer influences that reinforced its adoption. Similar to the baseline, the mixed and feminine forms take off in the early 80s and early 90s, and behave similar to the baseline throughout. As column 2 of Table VII shows, by 2019 the plural form is 7 percentage points more popular than in the baseline simulation (and the data), while the masculine form is 4 percentage points less so, and the feminine and mixed forms are each 1 percentage point less popular (see column 2 in Table VII). This exercise illustrates the importance of peer effects: they help entrench the status quo (in their absence the early popularity of the masculine form would have been lower), but they also magnify the impact of external influences (in their absence, the more innovative writing styles would have been less popular today). Thus, over the long-run peer influences have been a force sustaining diversity of choices in the profession.

Motivated by this discussion, in Figure X we present an exercise to quantify how peer influences interact with external trends to drive norm evolution. We vary the strength of peer influences across three scenarios (one for each curve): no peer effects, the peer effects we estimated, and peer effects as strong as those of Osborne-community women (the group with the largest estimated β's). We also vary the strength of the external influences across eleven scenarios (along the horizontal axis): we set a parameter $\pi \in \{0, 0.1, ..., 1\}$, and and for each scenario make the time effects be $\pi\varphi_t^\rho + (1-\pi)\varphi_{1970}^\rho$. $\pi = 0$ corresponds to the 'societal trends frozen to 1970' scenario as in panel b in Figure IX, while $\pi = 1$ corresponds to the baseline scenario under the estimated external trends as in panel a. We report the long-run (2017-2019) state of the writing norm. To keep the figure one-dimensional, the vertical axis reports the average entropy of the writing norm distribution, normalized to be between 0 and 1.[31] In this way, values close to 1 imply states with very diverse writing styles, while values close to 0 imply states where one writing style is dominant.

Regardless of the strength of peer influences, entropy increases as the strength of external trends grows. This is unsurprising since these trends have evened out preferences across writing styles. The figure reveals, however, that when external influences are week (π is small), professional networks subject to stronger peer influences observe much lower diversity of choices in the long run: In the absence of external forces pushing choices away from the status quo, strong conformity reinforces it. As external influences become more salient, however, the professional networks subject to stronger peer influences increase their long-run entropy faster than those without peer effects. This is because the stronger peer effects magnify the spread of the more innovative choices introduced by the external influences. The gap effectively closes at $\pi = 1$, and indeed, there entropy is higher under the estimated peer effects (red) than under no peer effects (blue).

In section 2 we discussed the surprisingly small differences in writing styles across cohorts of economists. To explore this further, we conclude our discussion around peer effects with a simulation exercise where we only allow peer influences among authors belonging to the same cohort.[32] We report its results in panel d of Figure IX and column 5 of Table VII. We find very small differences relative to our baseline simulation. This suggests that the small differences in behavior across cohorts result from small inter-cohort differences in preferences rather than being driven by differentially strong inter-cohort peer influences.

[31] Using the estimated choice probabilities for each article $(p_a^m, p_a^f, p_a^x, p_a^p)_t$, we compute the article's entropy as $E_{a,t} = -\sum_{\rho \in \{m,f,x,p\}} p_a^\rho \log(p_a^\rho)$, and average over all articles published in 2017-2019. We further normalize by the maximum possible entropy ($log(4)$):

$$H = \frac{\sum_{a,t \in \{2017-2019\}} E_{a,t}}{\sum_{a,t \in \{2017-2019\}} 1} \frac{1}{log(4)} \in [0, 1].$$

[32] We do this by recursively computing r_{it}^ρ values that exclude from the averages the writing style choices of authors belonging to cohorts different than i's.

Quantifying the role of compositional changes. In section 2 we also discussed a series of remarkable changes over the last half century: a steady increase in the share of women and in the number of economists, and a steady rise in the rate of academic collaboration. Later we documented a modest but significant increase in the share of the relatively more liberal, Osborne-community economists. We now investigate the extent to which these changes influenced the dynamics of writing norms. We first consider an experiment where we freeze the overall composition of the profession to mirror that of 1970: 2 percent of women (rather than the actual 10 percent), and 41 percent of Osborne-type economists (rather than the actual 48 percent). Panel e of Figure IX and column 3 of Table VII present the results under these counterfactual demographics. While the patterns over time are similar to the baseline predictions, by 2019 the masculine form would be 4 percentage points more popular, while the more innovative forms, feminine and mixed, would be 3 and 1 percentage points less popular. The direction of these results is not surprising, but the exercise reveals that the demographic change experienced over the last 50 years was not the main force driving the change in norms. This is in part because the conformism in the profession played a countervailing role dampening the impact that the demographic change could otherwise have had.

Earlier we mentioned the prevalence of homophily in collaborations. In our data, 82 percent of articles have same-community authors.[33] Mixed-sex collaborations, in contrast, occur frequently (12 percent, compared to the 9 percent that would prevail under at-random co-authoring). Homophily in co-authorship may mediate the norm dynamics because it limits interaction among different-minded academics. Panel f of Figure IX and column 6 of Table VII present the results of a simulation exercise where we make all collaborations in the data be between opposite community and opposite sex authors (e.g., Rubinstein man with Osborn woman, etc.) effectively eliminating homophily along those two dimensions. By 2019, the masculine form is 4 percentage points more popular than in the baseline simulation, and the feminine form is 4 percentage points less popular. While a first sight surprising, this result highlights the interaction between homophily and bargaining. The 'no homophily' counterfactual eliminates collaborations between pairs of Osborne-type economists and pairs of women, the ones most likely to make less traditional choices. In the simulated mixed collaborations, in contrast, these economists tend to accommodate the preferences of their co-authors. Thus, by allowing collaborations between economists with stronger preferences over more innovative styles, homophily allows those preferences to be expressed as choices. The broader lesson here is that diverse teams do not necessarily lead to more innovation if

[33] This is not surprising, of course, since the community detection model identifies the community labels off mutual co-authorship patterns in the professional network.

there are asymmetries in influence between team members.

6.2.3 Robustness: Choice-specific unobservables

We have argued that the value of the choices in our writing-style model is purely social, obviating the need for choice-specific unobservables. We conclude exploring several avenues of possible 'fundamental' differences in the value of choosing some writing styles over others.

Beliefs about journal editors' preferences. If authors believe that journal editors prefer some writing styles over others and make editorial decisions accordingly, this will induce differences in the perceived value of alternative choices. One possibility is that authors pay attention to the sex composition of the editorial boards of journals, and make writing style choices accordingly if, for example, they believe male and female editors have different preferences over writing styles and act on them.

To test for this possibility, we collected information on the editorial board membership of the "top five" general interest journals and five other highly ranked theory journals, from 1970 to the present. We then estimated linear probability models for the choice of only-masculine pronoun form at the article level on the average number of women in the editorial board in the three years prior to a paper's publication. Naturally, in this exercise we can only include the subset of papers published in any of the ten journals for which we have editorial information. We report the results in Table VIII.

Column 2 reports estimates from a model that includes author fixed effects, using only within author variation across publications. Overall, the share of female editors does not predict gendered pronoun choice. In the remaining columns we explore whether there are differences between papers authored by men and women. We find no effects for men (columns 5 and 6), but large and positive effects for women, even in the specification that includes author fixed effects. Women are more likely to use a masculine only writing style when facing a larger share of female editors.[34]

Expectations of conformity by un-tenured professors. If writing styles are perceived to matter for publication and for career concerns, un-tenured economists may respond to such perceptions through their choices. The profession may expect, or may be perceived to expect, for example, more traditionalist attachments by younger economists. We test this

[34]This result may be surprising. Kosnik (2022), however, reports writing behavior among female economists that may be consistent with it. She studies writing style as measured by text sentiment in Economics articles published in prestigious journals, and finds that sentiment is more negative in papers written by women compared to men. She argues this is driven by career concerns, because papers with more negative writing styles tend to receive more citations.

possibility estimating linear probability models of gendered pronoun choice on a dummy variable equal to 1 for articles with at least an author in the first six years of his academic career. The top row of Table IX presents the results. Authors at an early stage of their career are more likely to chose the plural writing style (relative to all other three styles). This is the case in both the specifications without (col. 5) and with (col. 6) author fixed effects.

Differential changes women's preferences We did not find significant differences between men and women in their preferences or their psychological types. Research in other areas has found, however, that women may effectively express their preferences only once they constitute a large enough share of the relevant network (e.g., Owen and Temesvary (2018) in the case of bank boards). A possibility in our setting is that the small share of female economic theorists, particularly early on, has limited their ability to signal their preferences more strongly. Because the profession has seen a steady growth in the share of women, in Table A.XII we explore this possibility by estimating differences in the distribution of the Osborne dummy for women of different cohorts. We do not detect any significant differences across the cohorts.

Signaling preferences across degrees of journal prestige. Could authors believe some writing styles to be more or less appropriate at journals of different degrees of professional prestige and act accordingly? We test this possibility in Table IX estimating linear probability models of gendered pronoun choice on either the log ranking of the article's journal (second row), or a dummy variable equal to 1 for articles in either of the "top five" journals in the profession. Articles in more prestigious journals are less likely to use plural forms (col. 6) and more likely to use mixed forms (col. 8) even after including author fixed effects.

Underlying complementarities between sub-fields and writing styles. Could it be that authors' writing style choices respond to the paper's topic, as captured by it's sub-field within Economic Theory? For example, contract theory could be more amenable to the mixed writing style if the principal-agent dichotomy is projected onto the masculine-feminine binary. Or perhaps more abstract sub-fields may be more amenable to the plural form. We assess this possibility in Table X, where we present estimates of linear probability models of the different writing styles on theory sub-field dummies. Even-numbered columns present estimates from models that include author fixed effects, and reveal that authors are less likely to chose plural forms and more likely to chose mixed forms, when publishing in Collective decision-making, Game theory, Information economics, and Welfare economics.

Motivated by these findings, we estimate a specification of our writing-style model where we include the following variables as additional shifters of the choice-specific payoffs: i) a dummy variable equal to 1 if the article has at least one female author, ii) a dummy variable equal to 1 if the article has at last one un-tenured author, iii) the journal's ranking, and iv) a dummy variable for whether the article's sub-field is either Collective decision-making, Game theory, Information economics, or Welfare economics. Our main findings remain unchanged.

7 Conclusions

We study the transformation in writing styles within the academic community of economic theorists between 1970 and 2019. In this period, the choice of gender for third person pronouns in the publications of these academics has moved away from the almost exclusive use of the masculine form to the adoption of plural and feminine forms, revealing changing views about gender more broadly. During the same period, the profession saw a large expansion in its size, increased academic collaboration, and an increasing participation of women. Against this background, we use a discrete choice model of writing style to quantify the importance of peer influences within the professional network in driving these long term changes. As a source of exclusion restrictions to identify the peer effects, we build an underlying network of feasible connections in the professional network borrowing recent tools from the Natural Language Processing literature. Additionally, to control for author-specific preferences related to views on gender issues, we estimate a model of community detection that allows us to classify authors into different groups. While this model allows for the possibility of both conformist (positive peer effects) and contrarian (negative peer effects) economists, we find that the profession is overwhelmingly conformist and that women exhibit larger peer effects than men. We then show these peer effects matter quantitatively. Early on, they reinforced the overwhelming dominance of the masculine form, slowing down the adoption of new forms. As external trends trickled into the profession, the peer effects then magnified their influence leading to a long-run state of considerable diversity in styles. We further quantify the contributions of the entry of women, the prevalence of co-authorship, and inter-generational peer influences in the dynamic evolution of the writing norms we observe.

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8 Tables

	(1) Co-authors	(2) Acquaintances	(3) Non-coauthors	(4) All
Same ethnicity	0.38	0.23	0.16	0.16
	(0.49)	(0.42)	(0.36)	(0.36)
Same sex	0.77	0.76	0.71	0.71
	(0.42)	(0.43)	(0.45)	(0.45)
Common fields	1.41	1.00	0.29	0.29
	(0.98)	(0.91)	(0.56)	(0.56)
Age difference	9.20	10.89	13.67	13.67
	(8.83)	(9.16)	(10.72)	(10.72)
Citations difference	4,720	5,060	2,457	2,457
	(12,576)	(12,335)	(7,244)	(7,244)
Productivity difference	12.51	11.91	5.07	5.07
	(15.99)	(14.92)	(8.65)	(8.65)
Log productivity product	3.53	3.42	1.70	1.70
	(1.94)	(1.71)	(1.38)	(1.38)
Pairs	50,778	748,023	429,238,173	429,288,951

Table I: Pairwise Characteristics. The table reports means and standard deviations (in parenthesis) for a set of pairwise characteristics across pairs of economists in the professional network. Column (1) restricts the set to include only pairs of economist who co-authored together. Column (2) restricts the set to include only pairs of economists in each others acquaintance sets. Column (3) restricts the set to include only pairs of economists who never co-authored with each other. Column (4) includes all pairs of economists in the professional network.

Panel A	Transition matrix for all sequences of pairs of articles			
	Masculine	Feminine	Plural	Mixed
From/To	(1)	(2)	(3)	(4)
Masculine	0.52	0.06	0.24	0.18
Feminine	0.18	0.31	0.24	0.26
Plural	0.28	0.09	0.49	0.14
Mixed	0.28	0.14	0.20	0.38

Panel B	Implied stationary distributions			
	Masculine	Feminine	Plural	Mixed
	(1)	(2)	(3)	(4)
Overall	0.35	0.12	0.31	0.22
Only single-authored	0.43	0.09	0.29	0.19
Only 70s cohort	0.51	0.04	0.29	0.16
Only 80s cohort	0.39	0.08	0.33	0.20
Only 90s cohort	0.33	0.12	0.31	0.24
Only 00s cohort	0.29	0.16	0.30	0.25
Only 10s cohort	0.26	0.19	0.31	0.24

Table II: Overall transition matrix and stationary distributions. Panel A presents the implied transition matrix across all sequential pairs of articles. Panel B presents the implied stationary distribution for the transition matrix in Panel A (overall), and the transition matrices that restrict attention to sequential single-authored pairs of articles, and for all sequential pairs of articles by author cohorts. The corresponding transition matrices for the single-authored and cohort groups appear in Table A.XI.

	Fractional Multinomial Response Models		
	Social network: Co-authors and cited		
	Dep var: Share of articles by author i's social network using writing style		
	Masculine	Feminine	Mixed
	(1)	(2)	(3)
Δz_{it}^{m}	1.76	0.08	1.72
	(0.06)	(0.06)	(0.09)
Δz_{it}^{f}	2.12	6.67	4.65
	(0.04)	(0.14)	(0.08)
Δz_{it}^{x}	-0.15	2.81	1.27
	(0.08)	(0.11)	(0.04)
Obs.		68,837	
	Social network: Only co-authors		
	Dep var: Share of articles by author i's social network using writing style		
	Masculine	Feminine	Mixed
	(4)	(5)	(6)
Δz_{it}^{m}	1.01	0.57	1.04
	(0.06)	(0.03)	(0.04)
Δz_{it}^{f}	1.55	2.77	2.49
	(0.05)	(0.07)	(0.06)
Δz_{it}^{x}	0.59	1.40	0.97
	(0.07)	(0.06)	(0.03)
Obs.		68,837	
	Social network: Only cited		
	Dep var: Share of articles by author i's social network using writing style		
	Masculine	Feminine	Mixed
	(7)	(8)	(9)
Δz_{it}^{m}	2.10	0.37	1.84
	(0.06)	(0.07)	(0.09)
Δz_{it}^{f}	2.22	8.22	5.44
	(0.04)	(0.13)	(0.09)
Δz_{it}^{x}	-0.76	3.21	1.31
	(0.07)	(0.11)	(0.05)
Obs.		68,837	

Table III: Control Function Models of Pronoun Choice. The table presents coefficient estimates of the fractional multinomial choice conditional mean equations. The explanatory regressors measure the change in (weighted) average pronoun choice of peers of a given author's peers who are not his acquaintances. The baseline category is the plural form. The top panel considers co-authors and citees as peers. The middle panel considers only co-authors as peers. The bottom panel considers only citees as peers.

	Social network: Co-authors and cited			
	Masculine	Feminine	Mixture	Plural
	(1)	(2)	(3)	(4)
z_{it}^m	0.53	-0.01	0.03	-0.55
	(0.01)	(0.00)	(0.00)	(0.01)
z_{it}^f	-0.33	0.66	0.05	-0.39
	(0.02)	(0.01)	(0.01)	(0.01)
z_{it}^x	-0.03	-0.00	0.64	-0.61
	(0.01)	(0.01)	(0.01)	(0.01)
Authors FEs	Y	Y	Y	Y
R^2	0.62	0.62	0.60	0.48
F-statistic	578	382	337	122
	Social network: Only co-authors			
	Masculine	Feminine	Mixture	Plural
	(5)	(6)	(7)	(8)
z_{it}^m	0.40	-0.01	0.05	-0.44
	(0.01)	(0.01)	(0.01)	(0.01)
z_{it}^f	-0.12	0.48	0.07	-0.43
	(0.02)	(0.01)	(0.01)	(0.01)
z_{it}^x	-0.03	0.05	0.48	-0.50
	(0.01)	(0.01)	(0.01)	(0.01)
Authors FEs	Y	Y	Y	Y
R^2	0.40	0.37	0.39	0.41
F-statistic	102	139	72	46
	Social network: Only cited			
	Masculine	Feminine	Mixture	Plural
	(9)	(10)	(11)	(12)
z_{it}^m	0.54	-0.00	0.04	-0.57
	(0.01)	(0.00)	(0.00)	(0.01)
z_{it}^f	-0.48	0.83	0.09	-0.44
	(0.02)	(0.01)	(0.01)	(0.01)
z_{it}^x	-0.03	-0.01	0.71	-0.66
	(0.01)	(0.00)	(0.01)	(0.01)
Authors FEs	Y	Y	Y	Y
R^2	0.68	0.77	0.66	0.49
F-statistic	1003	1130	670	143
Obs.	84,434	84,434	84,434	84,434

Table IV: Robustness: Linear Models for Pronoun Choice. The table presents coefficient estimates of the within-author panel linear regression models for the four pronoun form shares. The explanatory regressors measure the (weighted) average pronoun choice of peers of a given author's peers who are not his acquaintances. The baseline category is the plural form. The top panel considers co-authors and citees as peers. The middle panel considers only co-authors as peers. The bottom panel considers only citees as peers.

Pairwise Covariate	Acquaintance Set Definition $Q_{10}(i)$	$Q_5(i)$	$Q_{20}(i)$
$\underline{\gamma}$			
Same ethnicity	1.03	0.92	1.13
	(0.10)	(0.08)	(0.12)
Same sex	0.24	0.23	0.25
	(0.12)	(0.10)	(0.14)
Common fields	0.76	0.67	0.85
	(0.05)	(0.04)	(0.06)
Age difference	-1.98	-1.64	-2.29
	(0.51)	(0.44)	(0.61)
Citations difference	-4.86	-4.65	-4.96
	(0.19)	(0.17)	(0.23)
Productivity difference	0.34	0.21	0.36
	(0.49)	(0.41)	(0.58)
Log Productivity Product	0.49	0.47	0.51
	(0.02)	(0.02)	(0.03)
$\underline{\Omega}$			
$\omega_{\ell\ell}$	0.18	0.34	0.09
	(0.01)	(0.02)	(0.01)
$\omega_{\ell c}$	0.02	0.05	0.01
	(0.01)	(0.01)	(0.01)
ω_{cc}	0.06	0.11	0.03
	(0.02)	(0.03)	(0.02)
Rubinstein-type share	0.56	0.55	0.57

Table V: Community Detection Estimates. The table presents maximum likelihood estimates of the covariates-adjusted stochastic block model for community detection (Feng et al., 2023). The first column presents results under the ten-closest acquaintance set definition. The second column presents results under the five-closest acquaintance set definition. The third column presents results under the 20-closest acquaintance set definition. The model is estimated on the 29,302 authors who co-authored at least once.

Panel A: Parameters			
	Masculine	Feminine	Mixed
	(1)	(2)	(3)
α (Intercepts)	-1.04	-0.74	-0.60
	(0.06)	(0.04)	(0.04)
δ (Osborne-type dummy)	-0.36	0.02	0.88
	(0.04)	(0.13)	(0.07)
λ (Control function)	0.13	0.28	0.14
	(0.06)	(0.03)	(0.03)
ω (Bargaining power)			
Age diff.		1.10	
		(0.62)	
Citations diff.		-1.19	
		(0.89)	
Productivity diff.		-2.30	
		(0.59)	
Sex diff.		0.01	
		(0.17)	
Same ethnicity		-0.14	
		(0.11)	

Panel B: Peer effect heterogeneity			
Community	Sex	μ	σ
	Men	1.63	
Osborne		(0.16)	
			0.03
			[0.003 , 0.31]
	Women	1.92	
		(0.17)	
	Men	1.54	
Rubinstein		(0.14)	
			0.02
			[0.002 , 0.15]
	Women	1.55	
		(0.16)	
Observations		56,239	

Table VI: Parameter Estimates of the Writing Style Model. The table presents the parameter estimates from the multinomial choice model that considers both (weighted) past co-authors and past citees as peer influences, estimated using simulated maximum likelihood. The corresponding time effects are reported in Figure VII. The first four rows report choice-specific parameters. The parameters on the bargaining weights and the peer effect distributions are common across choices. The table reports standard errors for all parameter estimates except for the standard deviations of the peer effect distributions. For those we report confidence intervals that rely on the delta-method.

	Percentage points difference relative to baseline share in 2019					
	Baseline (1)	Freeze to 1970 (2)	No Peer Effects (3)	Own cohort peers (4)	Freeze 1970 types (5)	No Homophily (6)
Masculine	0.19	0.60	-0.04	-0.00	0.04	0.04
Feminine	0.23	-0.23	-0.01	-0.01	-0.03	-0.04
Mixed	0.26	-0.24	-0.01	0.02	-0.01	0.00
Plural	0.32	-0.14	0.07	-0.01	0.00	-0.00

Table VII: Simulated end-line writing style shares under alternative scenarios. The table presents the difference in the average distributions of pronoun form shares by 2019 relative the the baseline simulation using the estimated parameters from Table VI, under alternative scenarios. The first column presents the end point distribution under the baseline stationary simulation. The second column freezes the external trends to 1970 ($\varphi_t^\rho = \varphi_{1970}^\rho$). The third column supposes no peer effects ($\beta_i = 0$). The fourth column restricts peer influences to exist only between members of the same cohort. The fifth column freezes the sex and community-type distributions to their 1970-73 averages. The last column supposes no homophily in co-authoring ($\omega = 1$). In all simulations, the observed co-authorships are held fixed.

	Dependent variable: Only masculine pronouns dummy					
	Overall		With female author(s)		With only male authors	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure	0.16	-0.07	0.75	1.59	0.08	-0.15
	(0.07)	(0.12)	(0.20)	(0.61)	(0.08)	(0.12)
Year FEs	Y	Y	Y	Y	Y	Y
Journal FEs	Y	Y	Y	Y	Y	Y
Author FEs	N	Y	N	Y	N	Y
Obs.	10,918	6,804	1,465	519	9,453	6,013

Table VIII: Exposure to Female Editors. The table presents linear probability models at the article level estimated by OLS, on the sub-sample of articles published by the authors from our theorists professional network in one of ten major Economics journals (top-5 general interest and the top 5 economic theory journals based on *RePEC*'s rankings of September 2023). The exposure variable is the average number of female editors of in the board of a journal, over the three years period prior to an article's publication date. Besides year and journal fixed effects, odd-numbered columns also include the date of first publication, the total number of publications, the total number of citations, the ethnicity, and the community assignment (Osborne/Rubinstein) of each author. Columns (1) and (2) include all articles in any of the ten journals. Even-numbered columns include author fixed effects instead. Columns (3) and (4) only include articles with at least one female author. Columns (5) and (6) only include articles with both male authors.

	Masculine		Feminine		Plural		Mixed	
Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
First 6 Years	-0.022	-0.011	0.018	-0.005	0.022	0.023	-0.018	-0.007
	(0.004)	(0.007)	(0.002)	(0.004)	(0.004)	(0.007)	(0.003)	(0.006)
Log(Rank)	0.006	0.002	-0.001	0.001	0.016	0.008	-0.022	-0.011
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Top 5 Journal	0.019	0.006	0.005	-0.002	-0.073	-0.020	0.049	0.016
	(0.006)	(0.008)	(0.003)	(0.004)	(0.006)	(0.007)	(0.005)	(0.007)
Year FEs	Y	Y	Y	Y	Y	Y	Y	Y
Author FEs	N	Y	N	Y	N	Y	N	Y
Obs.	66,533	48,632	66,533	48,632	66,533	48,632	66,533	48,632

Table IX: Alternative Drivers of Writing Style Choices. The table presents coefficient estimates from linear probability models at the article level, separately regressing dummy variables for each type of writing style on three different variables. In the first row we report results for models that include a dummy variable equal to 1 if at least one author is, at the time of publishing the paper, at most 6 years since his first publication, as a proxy for the tenure track period. In the second row we report results for models that include the log rank of the journal where the article was published, based on the most recent ranking here: www.researchbite.com. It combines an h-index, an impact score, and the SJR score. In the third row we report results for models that include a dummy variable equal to 1 if the journal where the article was published is either *Econometrica*, *The Review of Economic Studies*, *The Journal of Political Economy*, *The American Economic Review*, or *The Quarterly Journal of Economics*. Odd columns present results for models without author fixed effects. Even columns present results for models with author fixed effects instead.

	Masculine		Feminine		Plural		Mixed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Analysis of Collective Decision-Making	0.038	0.018	0.053	-0.001	-0.234	-0.067	0.144	0.050
	(0.011)	(0.017)	(0.009)	(0.012)	(0.010)	(0.014)	(0.011)	(0.017)
Distribution	0.001	0.006	0.044	0.023	-0.012	-0.030	-0.033	0.002
	(0.027)	(0.038)	(0.021)	(0.027)	(0.029)	(0.039)	(0.020)	(0.034)
Financial Economics	0.027	0.005	-0.012	0.001	-0.035	-0.004	0.020	-0.003
	(0.007)	(0.011)	(0.004)	(0.006)	(0.007)	(0.010)	(0.006)	(0.009)
Game Theory	0.072	-0.012	0.037	-0.005	-0.232	-0.030	0.123	0.047
	(0.008)	(0.013)	(0.006)	(0.009)	(0.007)	(0.011)	(0.008)	(0.012)
General Equilibrium	0.090	0.022	0.019	0.006	-0.087	-0.011	-0.023	-0.018
	(0.016)	(0.021)	(0.011)	(0.014)	(0.016)	(0.020)	(0.012)	(0.017)
Household Behavior and Family Economics	-0.053	-0.057	0.016	-0.046	-0.096	-0.042	0.133	0.145
	(0.027)	(0.046)	(0.023)	(0.035)	(0.031)	(0.045)	(0.030)	(0.044)
Information, Knowledge, and Uncertainty	0.052	0.001	0.015	-0.003	-0.239	-0.064	0.172	0.066
	(0.009)	(0.014)	(0.007)	(0.010)	(0.008)	(0.011)	(0.009)	(0.014)
Market Structure, Pricing, and Design	-0.005	0.012	0.012	-0.004	-0.062	-0.010	0.055	0.001
	(0.008)	(0.013)	(0.006)	(0.009)	(0.009)	(0.013)	(0.007)	(0.012)
Micro-Based Behavioral Economics	-0.032	0.010	0.046	0.010	-0.147	-0.052	0.132	0.032
	(0.023)	(0.041)	(0.020)	(0.032)	(0.024)	(0.034)	(0.025)	(0.046)
Production and Organizations	-0.020	0.055	-0.032	-0.018	-0.040	-0.038	0.091	0.002
	(0.017)	(0.027)	(0.011)	(0.015)	(0.018)	(0.024)	(0.016)	(0.025)
Welfare Economics	0.026	-0.003	0.067	0.021	-0.177	-0.048	0.084	0.030
	(0.012)	(0.017)	(0.010)	(0.012)	(0.011)	(0.016)	(0.012)	(0.016)
Year FEs	Y	Y	Y	Y	Y	Y	Y	Y
Author FEs	N	Y	N	Y	N	Y	N	Y
Obs.	66,533	48,637	66,533	48,637	66,533	48,637	66,533	48,637

Table X: Differences in pronoun style choice by sub-fields. The table presents estimates from linear probability models at the article level, separately regressing dummy variables for each type of writing style on sub-field indicators. Odd columns present results for models without author fixed effects. Even columns present results for models with author fixed effects instead.

9 Figures

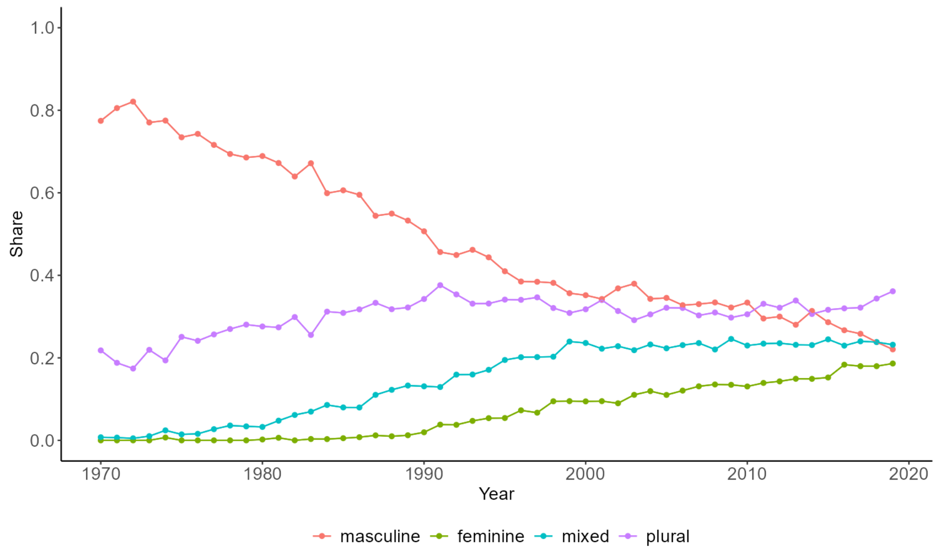
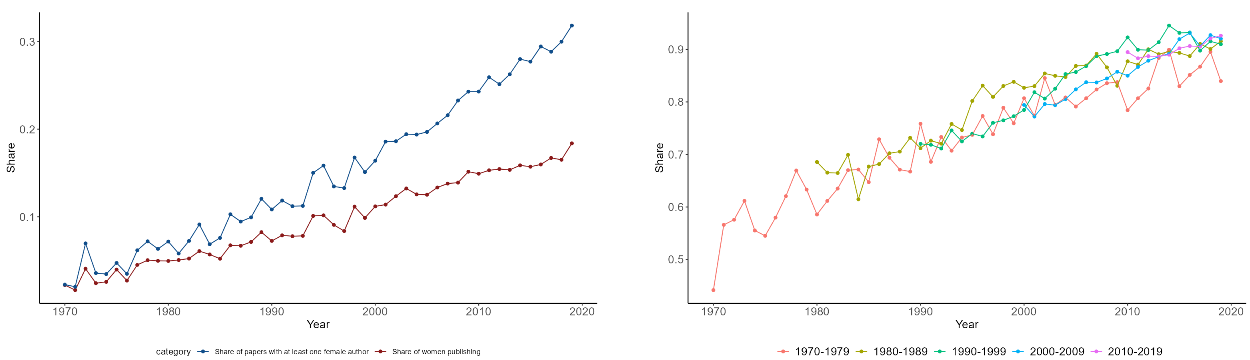
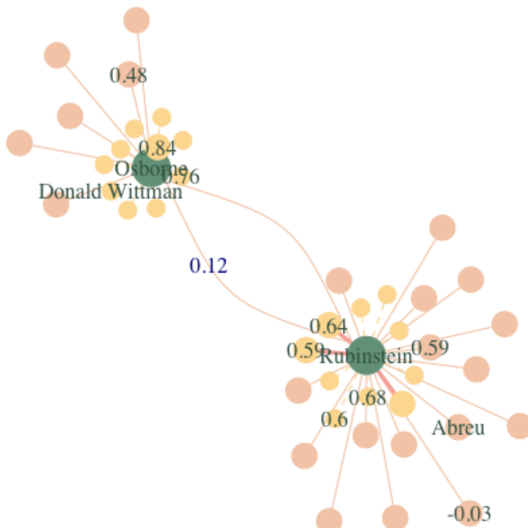


Figure I: Distribution of pronoun use over time in theory papers, 1970-2019.

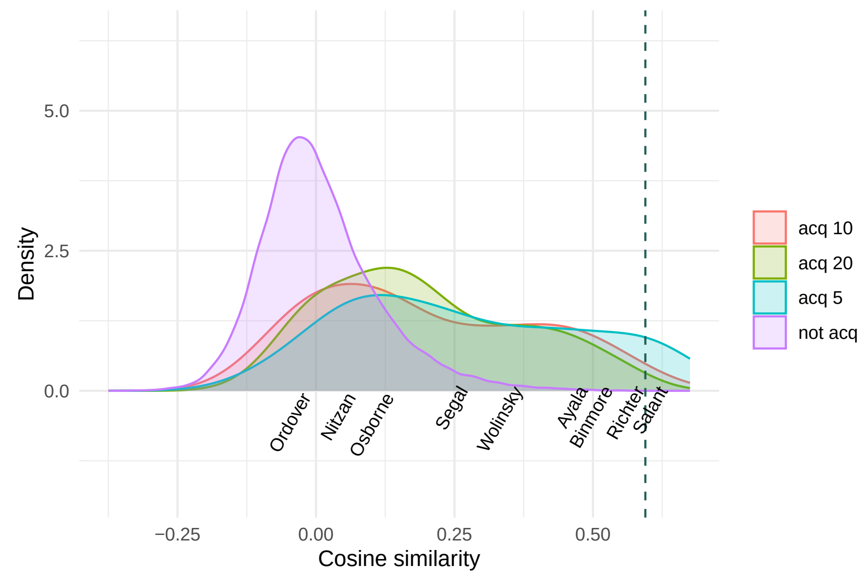


(a) Participation of women in the economic theory. **(b)** Share of co-authored papers, by cohort.

Figure II: Long-term change in the economics profession.



(a) Osborne and Rubinstein's local co-author network.



(b) Distribution of academic cosine similarity between Ariel Rubinstein and all other economists.

Figure III: Illustration: Ariel Rubinstein's and Martin Osborne's local peer network, and distribution of Ariel Rubinstein's academic similarities. In panel (a), solid edges represent co-authorships. Dashed edges represent acquaintances who are not co-authors. Yellow circles represent each author's ten closest authors in academic cosine similarity. The lengthier edges represent longer distances. In panel (b), A subset of Rubinstein's co-authors are marked along the x axis by their names; the density of his non-acquaintances appears in pink; the densities of his acquaintance sets appear in blue ($n = 5$), red ($n = 10$), and green ($n = 20$). The vertical dashed line represents the location of Rubinstein's tenth most similar author.

(a) Debraj Ray's network, 1993

(b) Debraj Ray's network, 1994

Figure IV: Example network and instrumental variables variation. The figure illustrates the instrumental variables variation induced by co-authors of co-authors who are not acquaintances of an author, for the case of Debraj Ray in 1993 and 1994. His co-authors appear in blue, his acquaintances appear in green, and non-acquaintances appear in pink.

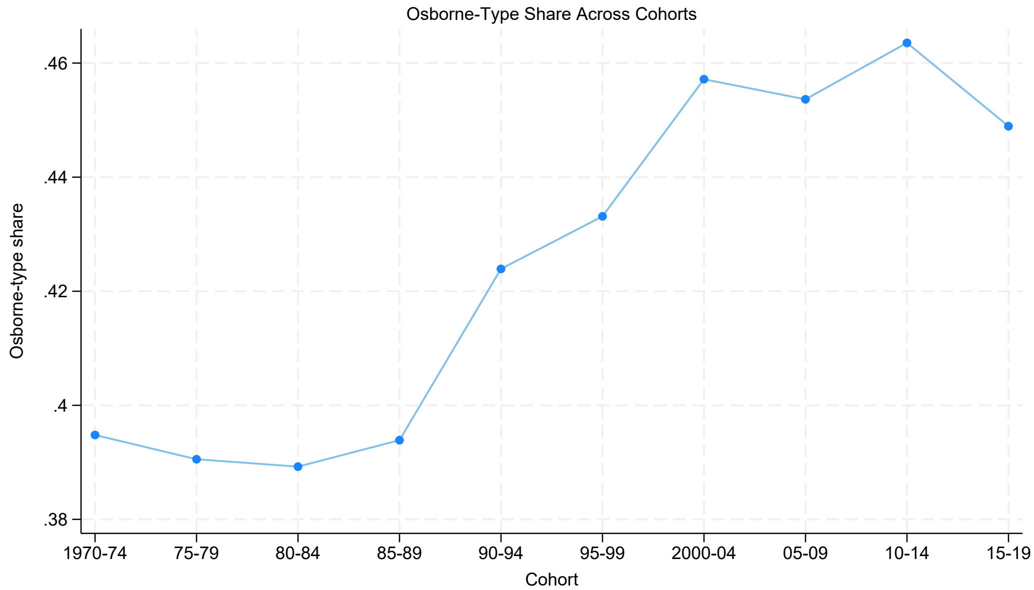


Figure V: Osborne Type Share across Cohorts. Share of authors assigned to Osborne's community, by 5-year cohorts of economists based on the community detection estimates based on the ten-closest acquaintance set definition.

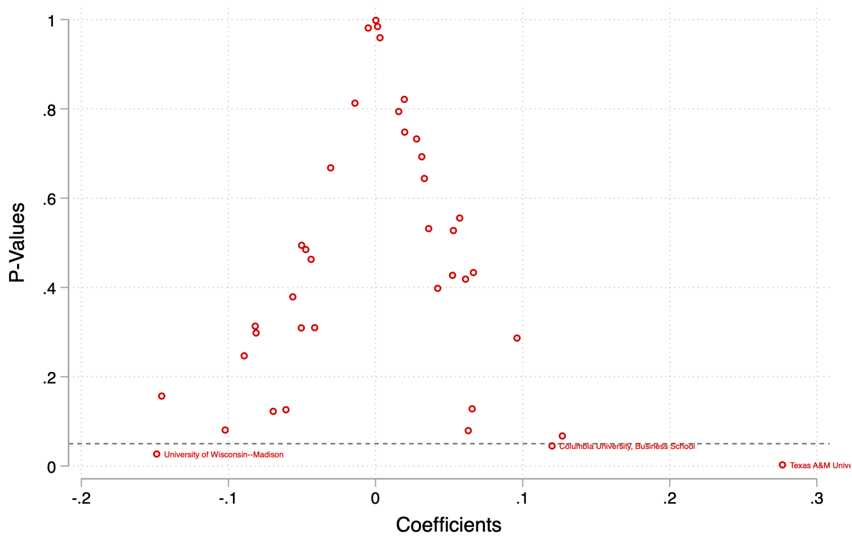


Figure VI: University affiliations and the Osborne-type dummy. Distribution of coefficient sizes and p-values by university to predict the Osborne-type dummy in a regression of 1,868 unique authors in 39 academic departments and 2,592 authors-x-department of the form: Osborne type dummy$_i$ $= a + \beta$Univeristy j dummy$_i + \epsilon_i$. The dashed line represents a p-value of 0.05.

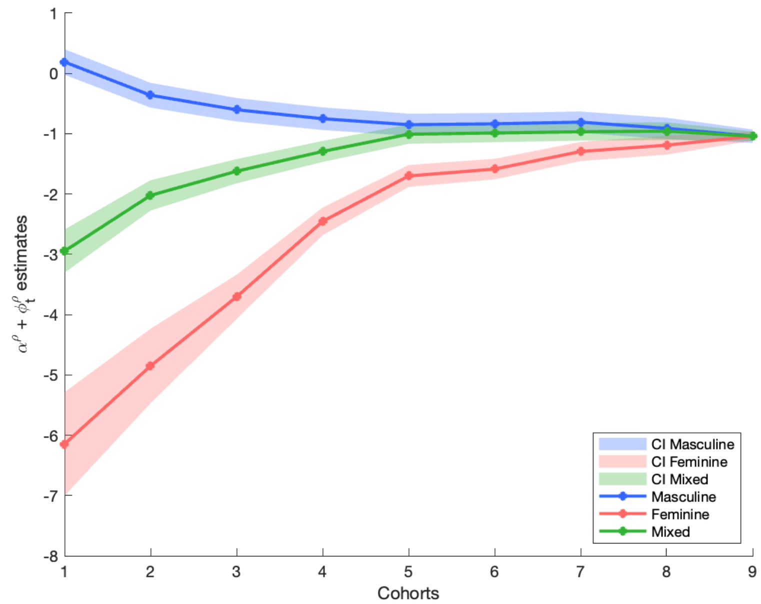


Figure VII: Time effects. Point estimates and 95% confidence bands for the writing-style-specific time-effect coefficients φ_t^ρ (plus the corresponding intercept α^ρ). We define time periods based on publication years, and group them as follows: 1970-79, 1980-84, 1985-89, 1990-94, 1995-99, 2000-04, 2005-09, 2010-14, 2015-19.

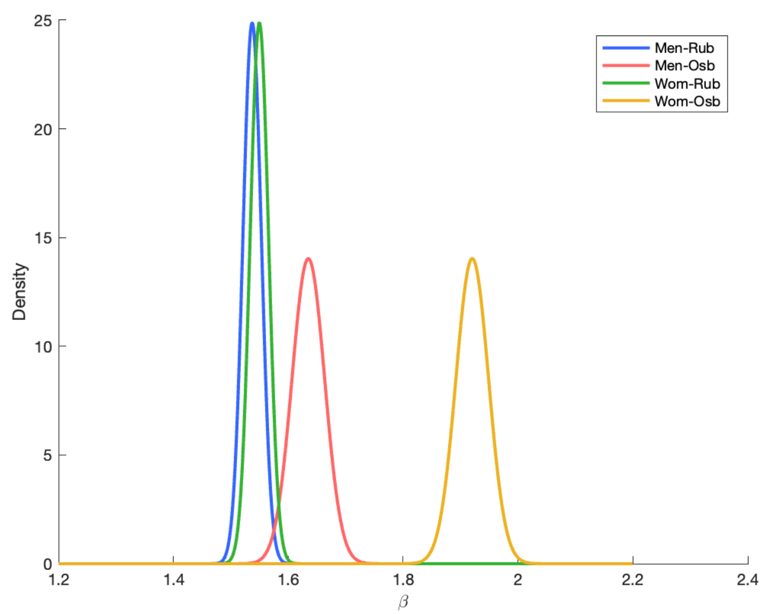
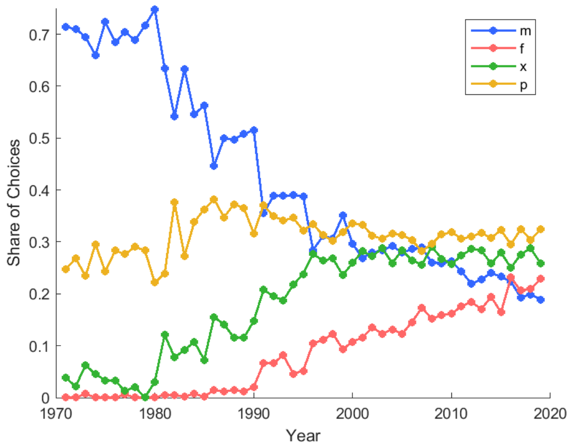
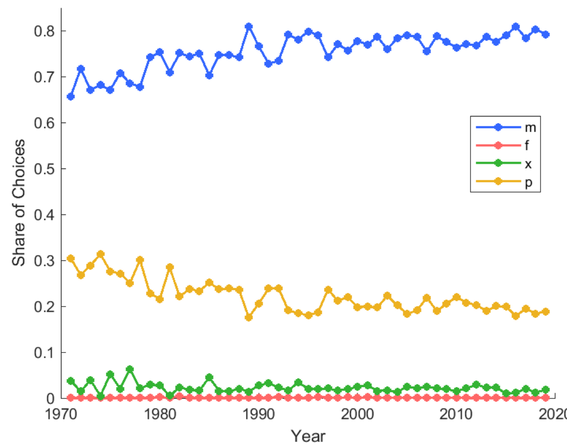


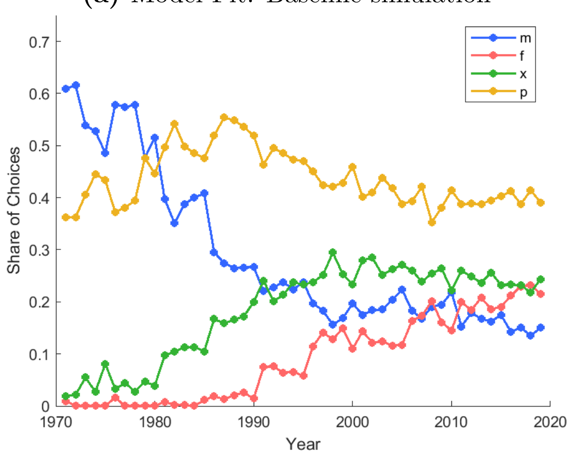
Figure VIII: Peer effects. Estimated Normal distributions of peer effect heterogeneity for Osborne and Rubinstein-type men and women economists. μ(Rub, men) $= 1.54$ (std.err $= 0.14$); μ(Rub, women) $= 1.55$ (std.err $= 0.16$); μ(Osb, men) $= 1.63$ (std.err $= 0.16$); μ(Osb, women) $=$ 1.92 (std.err $= 0.17$); σ(Rub) $= 0.02$ (confidence interval $= [0.002, 0.15]$); σ(Osb) $= 0.03$ (confidence interval $= [0.003, 0.31]$).



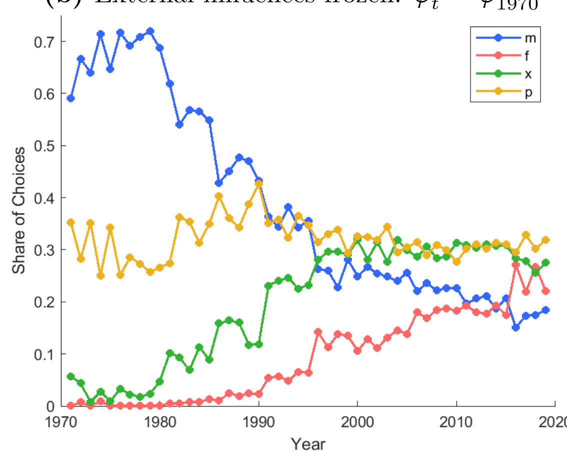
(a) Model Fit: Baseline simulation



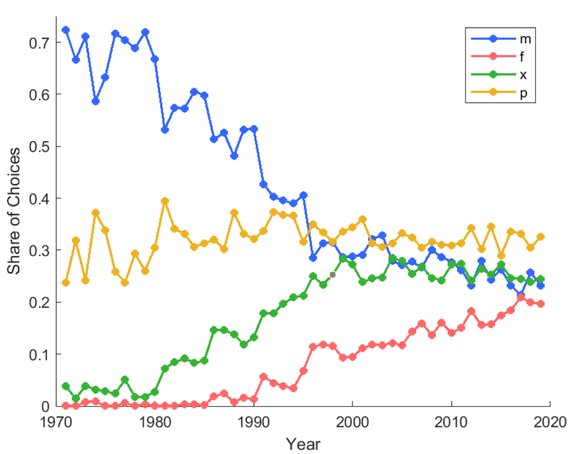
(b) External influences frozen: $\varphi_t^\rho = \varphi_{1970}^\rho$



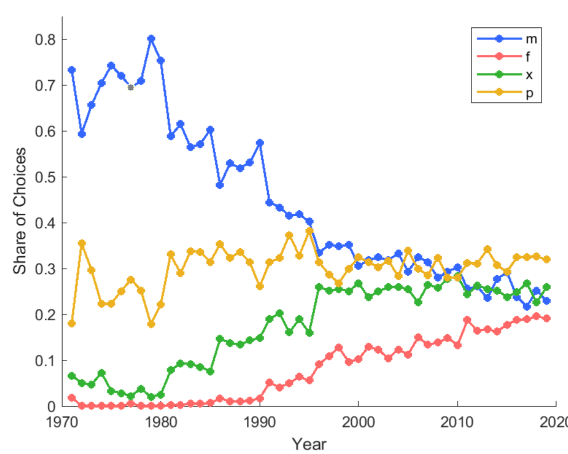
(c) No peer effects: $\beta^\rho = 0$



(d) Peer influences only from own cohort



(e) Type composition frozen



(f) No homophily

Figure IX: Simulated distribution of writing style choices over time: Alternative scenarios. The figures plot the time evolution of the aggregate distribution writing styles from simulated choices based on the estimated parameters from Table VI and alternative assumptions. As starting values for the peer influences, the simulation uses the observed average 1970-1974 distribution of choices.

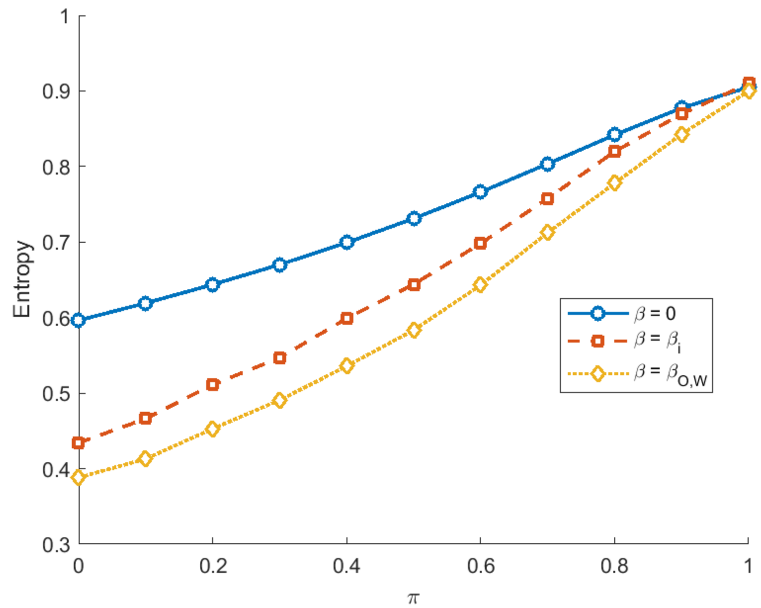


Figure X: Entropy Simulations. The figure plots the entropy of the distribution of choice probabilities averaged over 2017-2019 under alternative scenarios for the societal trend strength (horizontal axis) and peer effects strength (colored curves). The red curve corresponds to simulations using the estimates peer effects. The blue curve corresponds to simulations where peer effects are shut down. The yellow curve corresponds to simulations where peer effects for all economists are as strong as the estimated mean peer effects on Osborne-community women.

10 Online Appendix I: Additional Tables and Figures

	Masculine	Feminine	Plural	Mixed
From/To	(1)	(2)	(3)	(4)
Single authored				
Masculine	0.63	0.03	0.21	0.13
Feminine	0.14	0.43	0.20	0.23
Plural	0.32	0.07	0.50	0.11
Mixed	0.28	0.11	0.19	0.42
70s cohort				
Masculine	0.65	0.02	0.22	0.10
Feminine	0.22	0.27	0.21	0.30
Plural	0.41	0.04	0.44	0.12
Mixed	0.33	0.07	0.24	0.35
80s cohort				
Masculine	0.54	0.04	0.25	0.17
Feminine	0.19	0.27	0.27	0.27
Plural	0.31	0.07	0.49	0.13
Mixed	0.31	0.11	0.22	0.36
90s cohort				
Masculine	0.48	0.07	0.24	0.20
Feminine	0.19	0.27	0.25	0.29
Plural	0.25	0.10	0.50	0.15
Mixed	0.28	0.14	0.20	0.38
00s cohort				
Masculine	0.46	0.09	0.23	0.22
Feminine	0.17	0.33	0.24	0.25
Plural	0.23	0.13	0.50	0.15
Mixed	0.26	0.17	0.18	0.39
10s cohort				
Masculine	0.41	0.12	0.24	0.23
Feminine	0.16	0.38	0.22	0.24
Plural	0.21	0.13	0.52	0.14
Mixed	0.24	0.19	0.18	0.39

Table A.XI: Sub-group transition matrices. Transition matrices for single-authored to single-authored papers, and for different cohorts of authors corresponding to Panel B of Table II.

	Osborne dummy
Woman	-0.021
	(0.053)
Woman × 1980	-0.050
	(0.061)
Woman × 1990	-0.009
	(0.057)
Woman × 2000	-0.001
	(0.055)
Woman × 2010	0.003
	(0.055)
Obs.	29302

Table A.XII: The table presents the coefficients and standard errors from a cross-sectional linear regression at the author level, of the Osborne dummy on a dummy for whether the author is a woman, and interactions of it with cohort dummies.

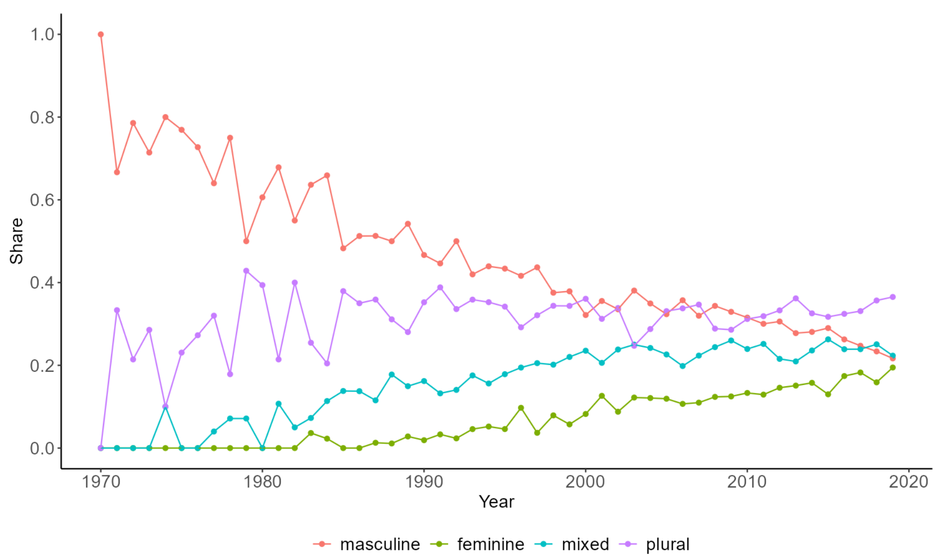
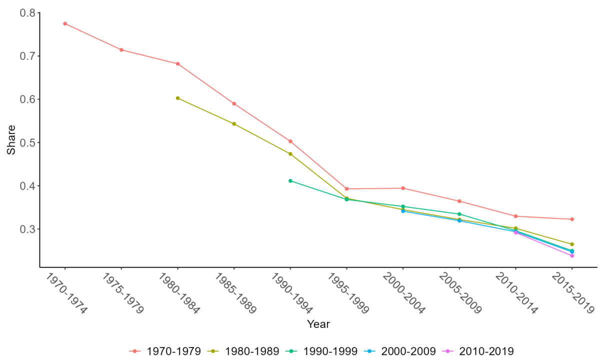
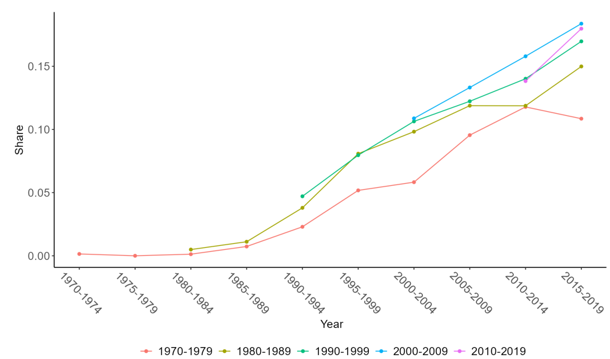


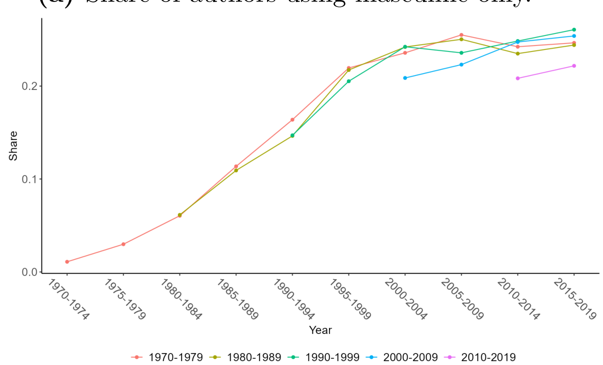
Figure A.XI: Distribution of pronoun use over time for papers authored by women, 1970-2019.



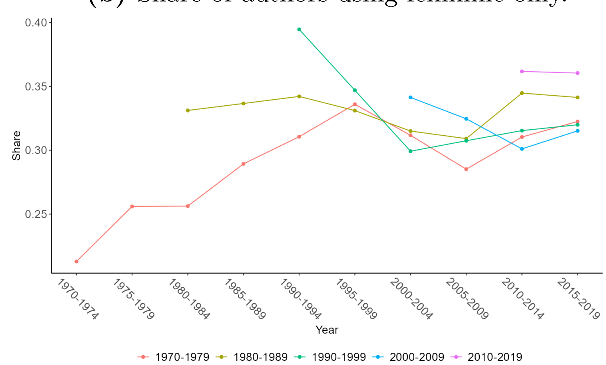
(a) Share of authors using masculine only.



(b) Share of authors using feminine only.



(c) Share of authors using mixed.



(d) Share of authors using plural only.

Figure A.XII: Distribution of pronoun use over time, by cohorts.

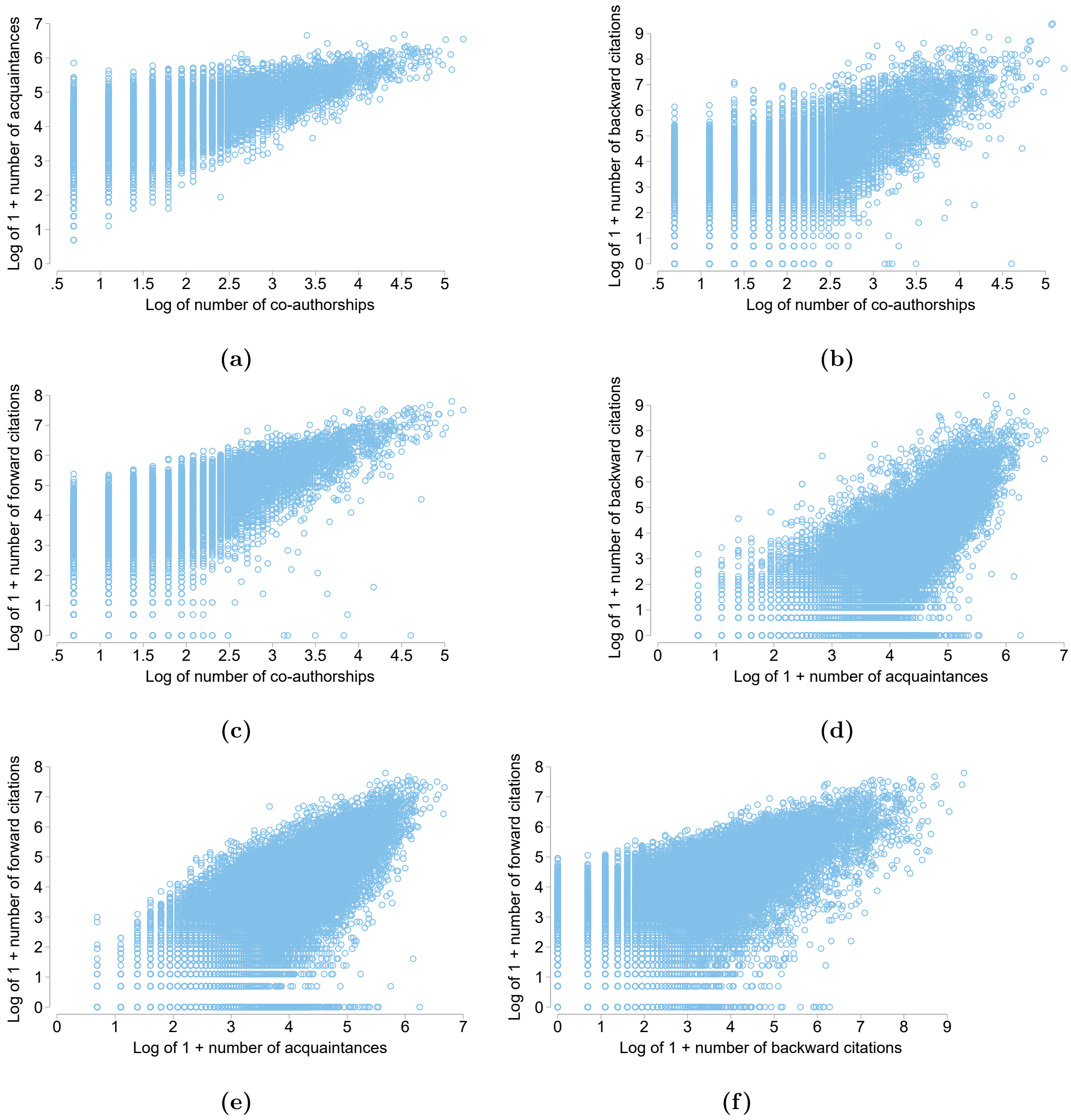
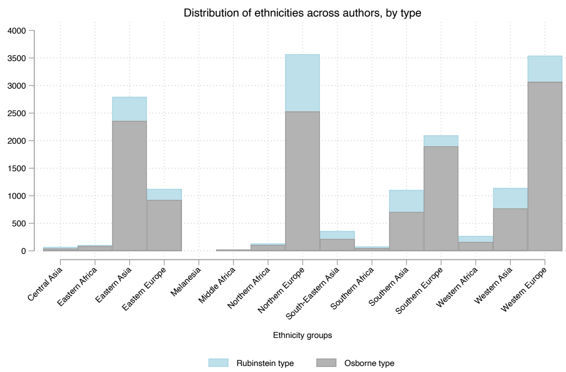
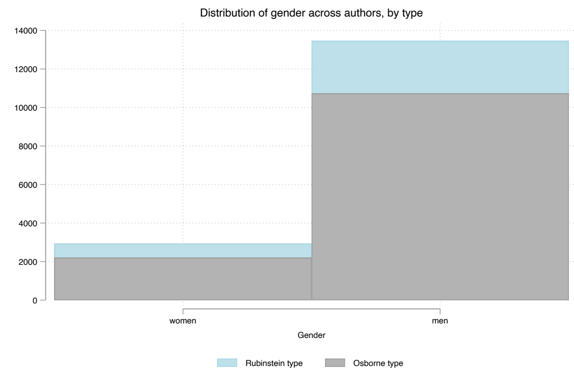


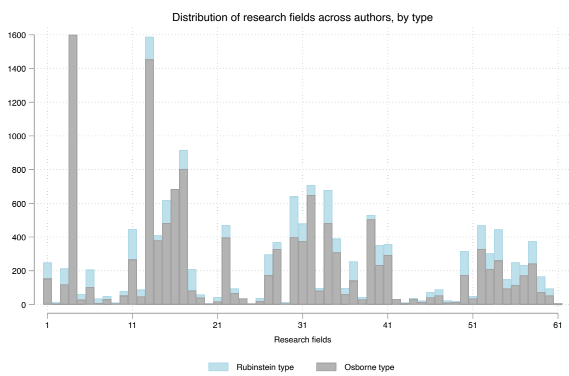
Figure A.XIII: Degree distributions across networks.



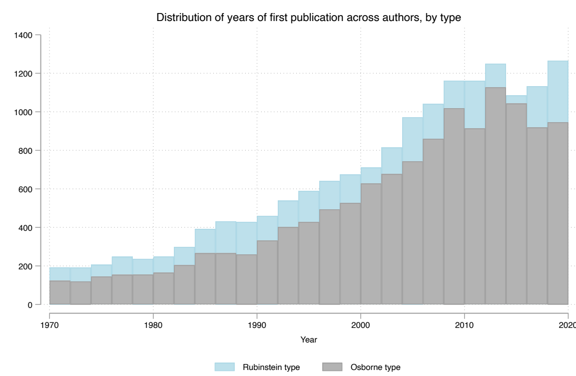
(a) Ethnicity



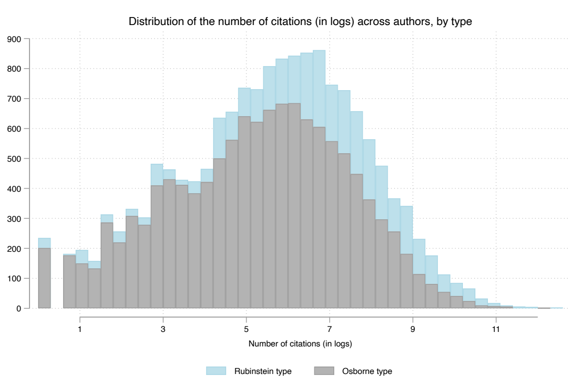
(b) Gender



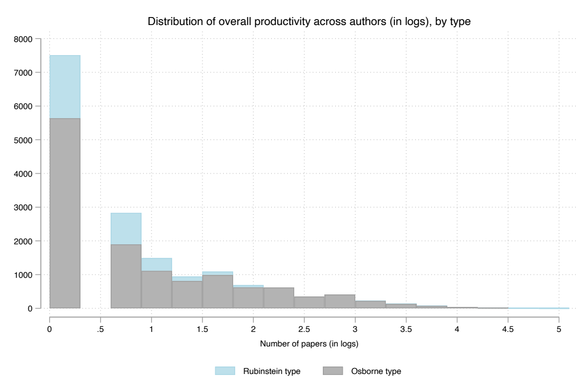
(c) Fields



(d) First publication



(e) Citations



(f) Productivity

Figure A.XIV: Distributions of author characteristics by community type assigned.

(a) Drew Fudenberg's network 1992

(b) Drew Fudenberg's network 1993

Figure A.XV: Example network and instrumental variables variation. The figure illustrates the instrumental variables variation induced by co-authors of co-authors who are not acquaintances of an author, for the case of Drew Fudenberg in 1992 and 1993. His co-authors appear in blue, his acquaintances appear in green, and non-acquaintances appear in pink.

11 Online Appendix II: Methodological Details

11.1 Selection of the sample of articles and authors

We use several sources to put together the sets of articles and authors that underlie our study. From *Jstor* and *Crossref* we obtained the metadata and the full texts of a large set of papers from Economics and Economics-related academic journals. We obtained the *Jstor* data under a data user agreement for the project. We obtained the *Crossref* data using their API.[35]

This resulted in 710 thousand articles. The set is over-inclusive, however. It contains papers in all fields of Economics, whereas our purpose is to put together a set of economic theory articles only. We implement a layered procedure to filter out articles unlikely to be theoretical, and to make sure we keep articles likely to be theoretical.

1. We exclude articles with corrupted metadata:

   - Missing a title.
   - Missing authors.
   - Missing the articles' text. These are articles for which our *Crossref* API retrieval generated a line of metadata but no associated article text. We inspected the list titles of this set of articles, and found 849 that we clearly identified as economic theory papers. We proceeded to directly retrieve the text of these articles, and included them back.

2. We exclude any article whose metadata suggests it is not a standard academic paper. This includes a reference to any of the following labels:

```
"Note from the editor"                   "Photograph"
"Meeting of the econometric society"     "Meetings of the econometric society"
"Accepted Manuscripts"                   "List of members"
"Announcement"                           "Announcements"
"Award"                                  "Awards"
"Front matter"                           "Back Matter"
"Book review"                            "Book reviews"
"Call for papers"                        "Distinguished fellow"
"Referees"                               "Editorial"
"Editor"                                 "Election of fellows"
"Errata"                                 "Erratum"
"Addendum"                               "Correction:"
"Correction to:"                         "Retracted Article"
"Corrigendum"                            "European meeting"
"Fellows"                                "Foreward"
```

[35] See https://www.crossref.org/education/retrieve-metadata/rest-api/. We used the R package `crminer` to retrieve the data. This package is no longer maintained, and to our knowledge, Crossref discontinued its open-access full-text retrieval service as of December 2020 -after we accessed it-.

```
"In memoriam"
"Report of the committee"
"Report of the director"
"Report of the managing editor"
"Report of the secretary"
"Submission"
"Thesis titles"
"Discussion"
"Foreword"
"Comment"
"Abstracts"
"IMACS"
"Note"
"Presidential address"
"Hardcover"
"Actuarial Vacancy"
"Secretary/Treasurer"
"ISBN"
"Conference"
"Verlag"
"Tribute"
"Listing Service"
"Contents of Volume"
"Obituary"
"Report on the adhoc committee"
"Report of the editor"
"Report of the representative"
"Report of the treasurer"
"Report of the President"
"Author index"
"Preface"
"Index"
"Contributors"
"Noticeboard"
"Reply"
"Rejoinder"
"Hardback"
"Paperback"
"Secretary-Treasurer"
"Treasurer"
"pp\\."
"Symposium"
"pages"
"(Eds)"
"Content of Volume"
```

3. We exclude all articles from academic journals that are either exclusively econometric or statistical, or from unrelated fields. Below is the list of journals whose articles we exclude:

```
"Econometric Theory"
"Econometrics Journal"
"Journal of Applied Econometrics"
"Journal of Econometrics"
"Physica A: Statistical Mechanics and its Applications"
"Statistics & Probability Letters"
"Stochastic Processes and their Applications"
"Applied Energy"
"Energy"
"Resources and Energy"
"Renewable Energy"
"The Electricity Journal"
"Marine Policy"
"Computational Statistics & Data Analysis"
"Mitigation and Adaptation Strategies for Global Change"
"Journal of Classification"
"World Patent Information"
```

"Social Indicators Research: An International and Interdisciplinary Journal for Quality-of-Life Measurement"
"Journal of Multivariate Analysis"
"Metrika: International Journal for Theoretical and Applied Statistics"
"Statistical Papers"
"Annals of the Institute of Statistical Mathematics"
"Journal of the Royal Statistical Society Series A"
"Journal of the Royal Statistical Society. Series C (Applied Statistics)"
"Journal of Time Series Analysis"
"Statistical Methods & Applications"
"Applied Mathematics and Computation"
"Mathematics and Computers in Simulation (MATCOM)"
"Global Finance Journal"
"Children and Youth Services Review"
"European Journal of Operational Research"
"Mathematical Methods of Operations Research"
"Mathematics of Operations Research"

4. We directly included in our final set all articles from strictly economic theory journals:

"Journal of Economic Theory"
"American Economic Journal: Microeconomics"
"Economic Theory"
"Games and Economic Behavior"
"International Journal of Game Theory"
"Games"
"Journal of Public Economic Theory"

5. For all other articles which had not been filtered out at this stage, we implement an algorithm to classify them as likely theoretical. For this purpose, we constructed a list of microeconomics keywords and a list of econometrics keywords.

   The list of microeconomics keywords is:

   game, player, utility, coalition, equilibrium,
   equilibria, rational, preference, core, Bayesian,
   pricing, welfare, marginal cost, theoretic, induction,
   signalling, strategic, bargaining, proposal, dynamic,
   Markov, subgame, monopoly, duopoly, oligopoly, cooperation,
   free rid, punish, design, contract, first best, second best,
   model, theory, theories, theoretical, auction, bid,
   dominance, risk, payoff dominant, backward induction, Cournot,
   Stackelberg, Nash, Aumann, unique, existence, multiplicity,
   pure, mixed, coordination, hawk, dove, battle of the sexes,
   battle of the sex, matching pennies, prisoner, efficient,

```
efficiency, evolutionary, replicator, dynamics, stable,
opponent, ambiguity aversion, strategies, payoffs,
expected utility, common knowledge, match, beliefs, intuitive
criterion, fixed point, delay, market design, zero-sum,
n-person, linear programming, Marshallian, compensated variation,
transitive, transitivity, club, Rules of thumb, rule of thumb,
Shapley value, Axiom, Axiomatic, Normal form, Extensive form,
Information set, Impossibility, Information structure,
private information, asymmetric information, moral hazard,
adverse selection, surplus, incentive constraint,
participation constraint, transferable utility, quasi-linear
```

The list of econometrics keywords is:

```
estimator, instrument, asymptotic variance, regression,
two stage least square, maximum likelihood,
generalized method of moments, multiple test, delta method,
continuous mapping theorem, measurement error, moment condition
```

(a) We include any paper containing at least 250 microeconomics keywords and no econometrics keywords.

(b) We include any paper satisfying all of the following criteria:

- Contains the word *proof* in its text.
- Contains at least ten microeconomics keywords.
- Contains ten times more microeconomics keywords as econometrics keywords.

(c) We then identify all authors from papers from (a) and (b), and among the remaining not-yet-included papers, we include those which satisfy the both of the following conditions:

- It includes authors from this list.
- it has ten times more microeconomics theory keywords as econometrics specific keywords, or has zero econometrics specific keywords.

This concludes the first component of the selection of papers into our sample, and yields 70062 articles written by 48626 authors.

6. At this stage, some of these 48626 author names correspond to differing spellings of the name of the same underlying author. We implemented an algorithm to find the alternative spellings of the same author, to then collapse these alternative spellings into a single author. First, we compute the frequencies of each name component (e.g., a first name, a last name, etc.) among all author names. We also extract the initials of each full name. We then identify, for each author, his least common name component (we call it the rare component). For example, for *Jean Marcal Tirole*, *Marcal* is its rare component, as its frequency is the smallest among the three components of this name. Next we split the sample of author full names into two sets. A set A of authors whose

rare component is unique in the data set, and none other of the components of their names are a rare component of any other author, and a set B with its complement.

The uniqueness of at least one word in the names of authors in set A implies they are highly unlikely to have duplicates. Set A has 8137 authors. In contrast, authors in set B have a rare component that is not unique in the data set. For each author $i \in B$, we produce a list of potential duplicates $D(i) = \{j, k, ...\} \subset A \cup B$ containing the author identifiers of each author sharing i's rare component. We then compare the initials of i's name to the initials of the names of every element of this potential match list to thin out these lists as follows: if j's initials are not a subset, a super set, or identical to the initials of i, we exclude j from the list. If the resulting match list for i is empty, we consider i to have no duplicates and hence to be unique. We identify 18413 authors as unique in this step.

For authors i for whom this procedure yields non-empty potential match sets $D(i)$, we further make pairwise comparisons of each of the name components of i to each of the name components of j with overlapping initials. If there is not at least one identical pairing among all these comparisons, we exclude j from the list in an additional thinning step. If the resulting match list for i is empty, we consider i to have no duplicates and hence to be unique. We identify 6336 authors as unique in this step. This leaves us with $15740 = 48626 - 8137 - 18413 - 6336$ author names i with potential duplicates $D(i)$, with corresponding initials and at least one identical name component from set B.

We then move to compare them to their potential duplicates using information about their articles. To do this, we first take the titles of the articles of each author i, and retrieve *ChatGPT* embeddings for each title separately, $\mathbf{e}_{ia}$, and for the grouping of all the titles of the author's articles, $\tilde{\mathbf{e}}_i$. For each pair of potential duplicate authors we compute the cosine similarity between each pairing of their articles and find the highest of these cosine similarities, s_{ij}^{max}. For each pair of potential duplicates authors we compute the cosine similarity between their grouped-titles embedding, $\tilde{s}_{ij}$. We then apply the following rule:

(a) If authors i and j share the same rare component (stronger signal), and $min\{s_{ij}^{max}, \tilde{s}_{ij}\} \geq 0.8$, consider i and j to be the same author.

(b) If authors i and j share a name component that is not the rare one for one of the authors (weaker signal), and $min\{s_{ij}^{max}, \tilde{s}_{ij}\} \geq 0.9$, consider i and j to be the same author.

(c) Otherwise, consider i and j to be unique distinct authors.

We chose the cutoff values for these rules by inspecting the sample and trade-off type 1 and type 2 errors as best as possible. In this way, we incorporate information from both the pair of authors' names and from the similarity in their articles, to assess whether they are actually the same individual.

For the remaining set of names i and potential duplicates $D(i)$ we find the most similar duplicate of i, $m_i = argmax_{j \in D(i)} \tilde{s}_{ij}$. We then find the most similar author to m_i: m_{m_i}.

If $m_i \neq m_{m_i}$, i.e., if the most similar duplicate of i does not have i as its most similar duplicate too, we consider them to be distinct authors unless $\tilde{s}_{im(i)} > 0.85$. Otherwise, we classify them as the same author. This final step is particularly useful for a handful of cases with a multiplicity of differing but closely similar name variations.

For the top 200 authors in our data set based on citations, we manually checked for alternative spellings of their names, and collapsed the duplicates accordingly. At this point we are left with 46655 unique authors.

7. Finally, we exclude articles missing their publication date, or with publication dates prior to 1970 or posterior to 2019. We also exclude articles that do not use any third person pronouns as described in subsection 11.2, and articles that do not have at least one known author matched to it.

This concludes our construction of the sample of articles and authors, and yields 73099 articles and 38046 unique authors.

11.2 Classification of the pronoun use style of articles: Allen NLP correferencing

Our methodology demands that we classify the writing style of each article as it relates to the gender choices for its third person pronouns. We rely on the *Allen* natural language processing (NLP) package, a state-of-the-art neural network model.[36] For each paper, we identify every instance of one of the following third-person pronouns: Masculine:

`he, him, his, himself.`

Feminine:

`she, her, hers, herself.`

Plural:

`they, them, their, theirs, themselves.`

Mix:

`he or she, him or her, his or her, himself or herself, he and she,`
`him and her, his and her, himself and herself.`

For each identified pronoun, we extract the sentence containing the pronoun, and the sentences preceding and following it. We then run the *Allen NLP* correferencing model on this text segment. This model relates the pronoun to its corresponding noun within the segment. For example, if we feed it the sentence "John ate an apple and he liked it", *Allen NLP* will indicate that "he" refers to John, and that "it" refers to apple. Figure A.XVI illustrates the form of the *Allen NLP* output, in a paragraph from an article in our sample.

[36] See https://demo.allennlp.org/coreference-resolution.

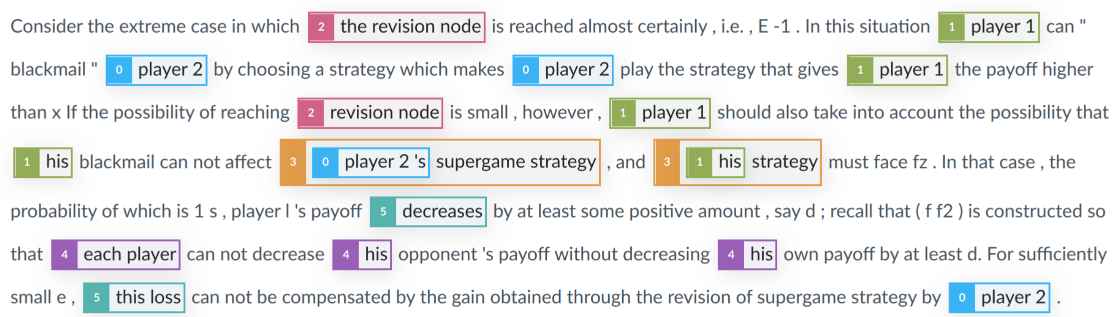


Figure A.XVI: *Allen NLP* correferencing example.

After parsing every segment involving a pronoun in an article, we obtain a list of proper nouns and their corresponding correferenced third-person pronouns in the article. *Allen NLP* is known to achieve at least a 75 percent accuracy in standard English text. At the paper level, our manual checks suggest an error rate of almost zero.

In a next step, we use a list of keyword economic agent nouns, to select the *Allen NLP* correferenced nouns in each paper that correspond to economic agents the articles are referring to. We use the following list:

```
'individual', 'worker', 'agent', 'principal', 'loser',
'representative','[pl]ayer', 'trader', 'competitor', 'winner',
'citizen', 'messenger', 'manufacturer', 'investor', 'bank',
'government', 'criminal', 'member', 'researcher', 'opponent',
'group', 'respondent', 'party', 'incumbent', 'buyer', 'legislator',
'officer', 'prisoner', 'insured', 'insurance', 'owner', 'lender',
'challenger', 'cooperator', 'employer', 'customer', 'participant',
'borrower', 'mover', 'recipient', 'household', 'innovator', 'leader',
'rival', 'follower', 'contestant', 'intermediaries', 'voter',
'dictator', 'ceo', 'monopolist', 'migrant', 'candidate', 'manager',
'peer', 'user', 'trustee', 'oligopolist', 'employee', 'firm',
'regulator', 'person', 'maker', 'auctioneer', 'type', 'intruder',
'outsider', 'insider', 'people', 'dealer', 'entrepreneur',
'policymaker', 'nature', 'negotiator', 'neighbo[r]', 'executive',
'physician', 'generation', 'child', 'parent', 'newcomer', 'friend',
'professional', 'retailer', 'resident', 'student', 'subject',
'seller', 'partner', 'bidder', '[c]onsumer', 'organization',
'those who', 'sender', 'receiver', 'stockholder', 'team', 'speculator',
'supplier', 'producer', 'labourer', 'laborer', 'landholder', 'farmer',
'developer', 'creditor', 'politician', 'planner', 'arbitrageur',
'committee', 'board', 'bargainer', 'herder', 'defendant', 'plaintif',
'jury', 'jurist', 'juror', 'judge', 'colleague', 'faculty', 'scientist',
'analyst', 'applicant', 'baron', 'bureaucrat', 'contractor',
'decision - maker', 'decisionmaker', 'decisions makers', 'entrant',
'expert', 'landlord', 'merchant', 'mutant', 'offender', 'peasant',
'proposer', 'purchaser', 'responder', 'teacher', 'venture capitalist',
```

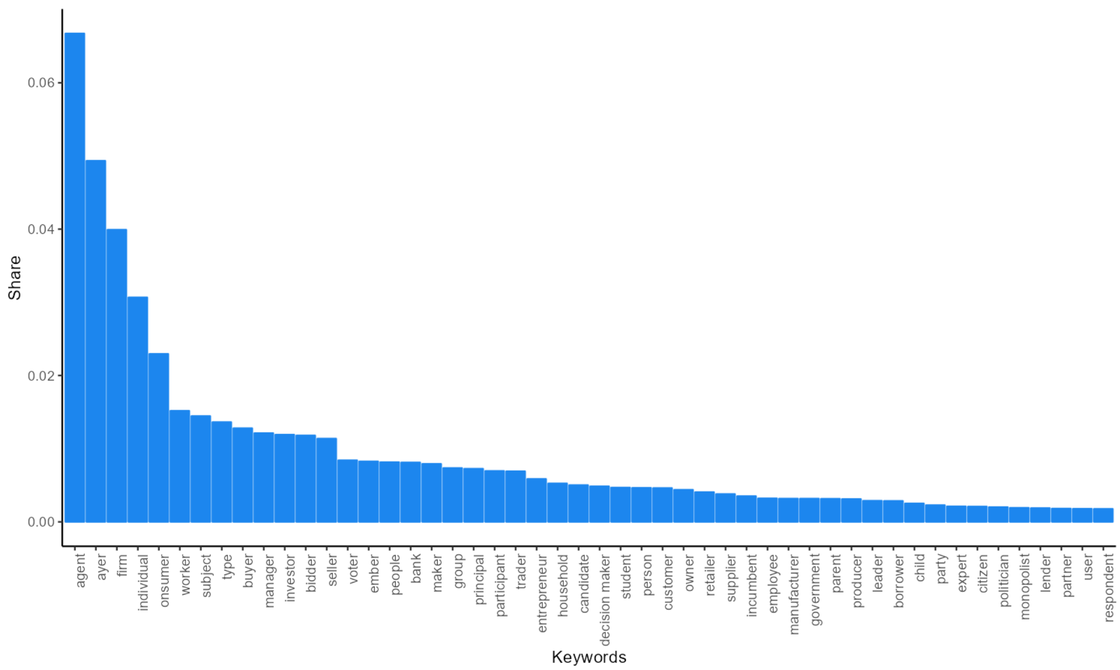


Figure A.XVII: Distribution of agent nouns used for co-referencing across articles: top 50.

`'tortfeasor', 'commuter', 'insurer'.`

After identifying all instances of pronoun use referring to any of the agent nouns listed above, we count the number of times masculine, feminine, plural, or a combination, are used in each paper to refer to them. Figure A.XVII presents the distribution of these agent nouns across the full sample of article texts, for the top 50 most frequently used agent nouns.

We classify an article as masculine if it only uses masculine pronouns. We classify an article as feminine if it only uses feminine pronouns. We classify an article as plural if it only uses plural pronouns. We classify an article as mixed if it uses mixed pronouns, or a combination of more than one type of pronoun.

11.3 Measurement of the relative spatial location of authors: *Author2vec*

To identify a set of plausible coauthors for each author in our sample, we adapted the *Word2vec* algorithm to our setting. *Word2vec* is a widely used algorithm in computer science designed to capture semantic relationships between words based on their co-occurrence patterns in a body of text (corpus). It is based on the distributional hypothesis proposition in linguistics, according to which words appearing in similar contexts tend to have similar meanings. Within a given corpus (e.g., the congressional record), it uses the relative frequencies with which pairs of words appear near each other (right before or after, within a few words of each other, etc.) to assign a high-dimensional vector of real numbers to each word –referred to as the word's *embedding*–.[37] We denote word i's embedding by $\mathbf{e}_i$. An embedding contains cardinal information about the word's meaning in relation to all other words in the corpus: words that are closer to each other in this vector space, say using a Euclidean distance norm, are deemed to be closer to each other in meaning, because the relative frequencies with which they appear near other words is similar.

Consider a word w_j in some sentence, and refer to it as the center word. Consider other words in the same sentence found at most m[38] words away from w_j, and refer to them as context words. Denote this set as $M(j)$. *Word2vec* allows for each word j to have an embedding as center word, $\mathbf{e}_j^c$, and an embedding as context word $\mathbf{e}_j^o$. *Word2vec* defines the conditional probability of observing context word w_k given center word w_j using the *softmax* function as

$$\mathbb{P}(w_k|w_j) = \frac{\exp(\mathbf{e}_k^{o\prime}\mathbf{e}_j^c)}{\sum_\ell \exp(\mathbf{e}_\ell^{o\prime}\mathbf{e}_j^c)}$$

Making the dot product between context word w_k and center word w_j large relative to all other words in the corpus makes this probability high.

Word2vec chooses the collection of vectors $\{\mathbf{e}_j^o, \mathbf{e}_j^c\}_{j=1}^W$ for all words in the corpus that maximizes the joint likelihood of observing the actual context-center pairs:

$$L(\theta) = \prod_{j=1}^{W} \prod_{k\in M(j)} \mathbb{P}(w_k|w_j)$$

The solution to this problem minimizes the difference between the predicted conditional probabilities and the actual distribution of word pairings in the corpus. In a final step one can average the estimated center and context embeddings of each word to obtain a single embedding for the word.

Word2vec is, implicitly, a network-based model where words are nodes, and edges between words exist when two words are near each other in the corpus –how near being a parameter chosen by the researcher–. The idea we propose here is to rely on the same logic, applied to the social network of economists in our sample, to measure 'academic similarity' across authors. We call this algorithm *Author2vec*. Authors play the role of words, cross-citation relationships play the role of edges between them, and we compute an embedding vector for each author[39]. Two authors with close embeddings will be authors who cite and are cited by similar subsets of other authors, in the same way that words with close embeddings are words that appear near similar subsets of other words. In this sense, such authors are nearby in 'academic' space, and we will rely on this academic distance to restrict the set of authors that could feasibly be co-authors of a given author.

To implement our *Author2vec* methodology we transform each article a in our data set into a vector $\mathbf{v}_a$ of author identifiers that includes identifiers for all authors that either co-authored the paper or that are cited in the paper. Each such vector is analogous to a sentence in standard *Word2vec*. The collection of all such vectors $\{\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_{N_a}\}$ constitutes

[37]Large language models such as *ChatGPT*, for example, rely on a corpus that may include all of the internet, and on embeddings of many thousands of dimensions.

[38]m is a radius chosen by the researcher. If $m = 1$, for example, we only consider the word directly preceding and the word directly succeeding w_j as context words.

[39]In practice we allow for 100-dimensional embeddings for the authors.

our corpus. We define a pair of authors to be 'near' if they appear in the same article vector. We can then use the frequencies with which each author is 'near' every other author within our corpus of articles in exact analogy to how *Word2vec* uses the frequency with which a given word appears before or after (near) every other word within the corpus of text.

We rely on the *Microsoft Academic Graph* (MAG)[40] and *Jstor* data sets to retrieve network-related information about the set of authors in our sample, including co-authorship relationships and forward and backward citation relationships.

11.4 Construction of the acquaintance sets

We rely on the author embeddings from our *Author2vec* methodology to compute the cosine similarity (dot product of two vectors divided by the product of their lengths) between each pair of authors in our sample, $s_{i,j}$, as a scalar measure of academic proximity[41]:

$$s_{i,j} = \frac{\mathbf{e}_i'\mathbf{e}_j}{|\mathbf{e}_i||\mathbf{e}_i|}$$

Our premise is that pairs of authors far from each other in this academic space are effectively unable to consider each other as potential co-authors. We compute an acquaintance set of potential co-authors for each author, $Q_n(i)$, as follows: we take the union of the n closest authors to author i, all co-authors of author i, and the n closest authors to each of i's co-authors. We then exclude from this set any author who does not overlap in his productive years –defined as the range of years between three years before the author's first publication and five years after the author's last publication–, with author i. By construction, $Q_n(i)$ includes all authors who did co-author with i at some point and a number of other authors who did not, but who are close enough in academic space that it is likely i could have considered them as co-authors. Our benchmark estimates use acquaintance sets with $n = 10$, but we also set $n = 5$ or 20 in alternative specifications.

11.5 Measurement of covariates

11.5.1 Assignment of sub-fields for authors: *ChatGPT* embeddings

Co-authorship decisions are likely influenced, among other characteristics, by the overlap in the sub-fields of study of authors. We assign sub-fields of specialization to the authors in our sample as follows: first, we borrow the *Journal of Economic Literature* (JEL) fields classification, and select a subset of the JEL fields which we deem relevant in our context. The following is the list of JEL fields we use:

- C6 Mathematical Methods • Programming Models • Mathematical and Simulation Modeling
- C7 Game Theory and Bargaining Theory

[40] See https://www.microsoft.com/en-us/research/project/microsoft-academic-graph.

[41] Cosine similarity is the most commonly used distance measure in the network science-large language models literature.

- C9 Design of Experiments
- D1 Household Behavior and Family Economics
- D2 Production and Organizations
- D3 Distribution
- D4 Market Structure, Pricing, and Design
- D5 General Equilibrium and Disequilibrium
- D6 Welfare Economics
- D7 Analysis of Collective Decision-Making
- D8 Information, Knowledge, and Uncertainty
- D9 Micro-Based Behavioral Economics
- E2 Consumption, Saving, Production, Investment, Labor Markets, and Informal Economy
- E3 Prices, Business Fluctuations, and Cycles
- E4 Money and Interest Rates
- E5 Monetary Policy, Central Banking, and the Supply of Money and Credit
- E6 Macroeconomic Policy, Macroeconomic Aspects of Public Finance, and General Outlook
- E7 Macro-Based Behavioral Economics
- F1 Trade
- F3 International Finance
- G1 General Financial Markets
- G2 Financial Institutions and Services
- G3 Corporate Finance and Governance
- G4 Behavioral Finance
- G5 Household Finance
- H1 Structure and Scope of Government
- H2 Taxation, Subsidies, and Revenue
- H3 Fiscal Policies and Behavior of Economic Agents

- H4 Publicly Provided Goods
- H5 National Government Expenditures and Related Policies
- H6 National Budget, Deficit, and Debt
- H7 State and Local Government • Intergovernmental Relations
- H8 Miscellaneous Issues
- I1 Health
- I2 Education and Research Institutions
- I3 Welfare, Well-Being, and Poverty
- J. Labor and Demographic Economics
- K. Law and Economics
- L1 Market Structure, Firm Strategy, and Market Performance
- O1 Economic Development
- O2 Development Planning and Policy
- O3 Innovation • Research and Development • Technological Change • Intellectual Property Rights
- O4 Economic Growth and Aggregate Productivity
- P. Political Economy and Comparative Economic Systems
- R. Urban, Rural, Regional, Real Estate, and Transportation Economics
- Z1 Cultural Economics • Economic Sociology • Economic Anthropology

We then retrieve the *ChatGPT* embedding corresponding to all the words in the description of each of these fields, including the text descibing its subfields.[42] This gives us an embedding for each field j, $\bar{\mathbf{f}}_j$, with $j = 1, ..., J$. In parallel, for each author i in our sample we create a collection K_i of the words in the titles of all of i's articles, and the words in the titles of all papers cited in i's articles. Next we retrieve the *ChatGPT* embedding for the

[42]We retrieve ChatGPT-3 embeddings of 1536 dimensions, based on their text-embedding-ada-002 model. See https://openai.com/blog/new-and-improved-embedding-model. Because ChatGPT's embeddings are estimated for a large corpus of English text, they are ideal as measures of relative similarity between common-use words. One of the main advantages of LLM word embeddings is their cardinal nature, allowing arithmetic operations that preserve relative meanings. As an example often used in this literature, subtracting the embedding for the word *man* from the embedding for the word *king*, and then adding the embedding for the word *woman* yields an embedding that is remarkably close to the embedding for the word *queen*.

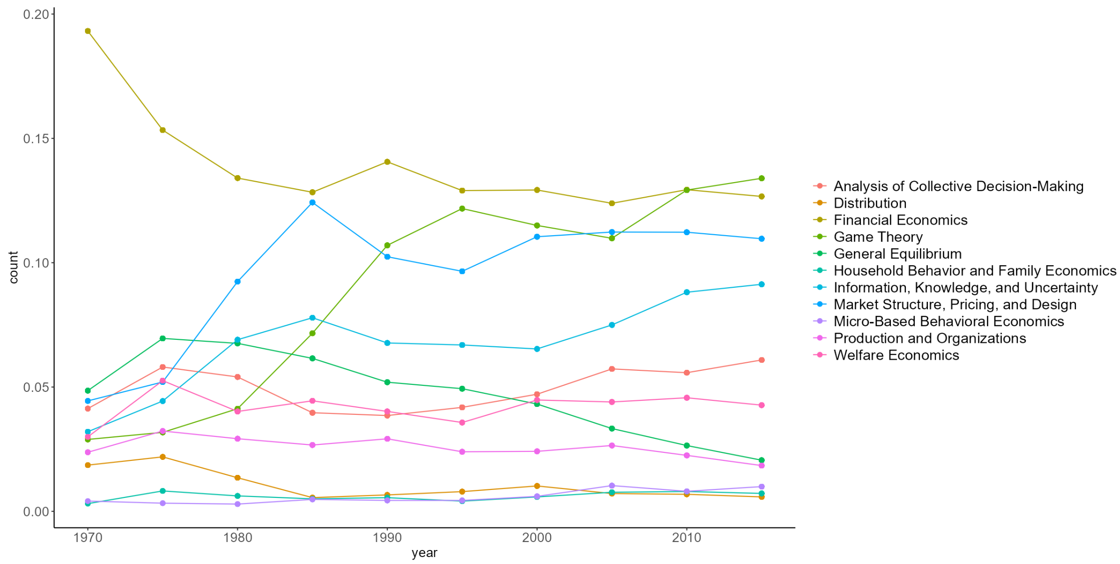


Figure A.XVIII: Distribution sub-fields by 10-year cohorts.

collection of all words in K_i. This gives us an average embedding for author i, $\overline{\mathbf{g}}_i$. Next we compute cosine similarity distances between each author and each field,

$$\sigma_{i,j} = \frac{\mathbf{g}_i'\mathbf{f}_j}{|\mathbf{g}_i||\mathbf{f}_j|}.$$

Finally, we assign to each author the three sub-fields with the smallest cosine similarity distances and use those to create dummy variables indicating sub-fielf membership.

In Figure A.XVIII we plot the distribution of sub-fields by 5-year cohorts of articles. Most fields have remained stable, with some exceptions: "Financial Economics" which fell from 20 percent to 13 percent in the 1970s and has remained stable since, and General Equilibrium has fallen steadily from 7 percent to 3 percent. In contrast, Game Theory and Market Structure, Pricing and Design grew rapidly in the 70 and 80s from less than 5 percent to around 12 percent today each. Information, Knowledge, and Uncertainty has also grown from 3 to 9 percent.

11.5.2 Classification of the of ethnic origin of authors: *Namsor*

We rely on the authors' full names we obtained directly from the articles in our data set to assign an ethnic origin to each author. We do this using *Namsor*[43], a software tool specialized in identifying the likely regions of origin of proper names and last names from cultures all around the world. For each component of an author's name –first name, middle name, last name– Namsor reports a most likely origin at the sub-region level (e.g., Western Europe, South-east Asia, Middle East, etc.). As the ethnic origin of author i, we assign the modal sub-region reported by Namsor across all of the author's name components. For the small subset of cases with ties, we relied on *ChatGPT* prompts containing Namsor's guesses, and

[43] See https://namsor.app.

retrieved *ChatGPT* best guess response. .

11.5.3 Classification of the gender of authors: Genderize package in R

We rely on the authors' first names we obtained directly from the articles in our data set to assign a gender to each author. We do this using the *Genderize* package in R,[44] a software tool that has been trained on a large corpus of text as a probabilistic gender classifier for first names. We face one challenge: first and last names appear in no particular order. Sometimes first names appear before last names, and sometimes the other way around. Thus, we proceeded by genderizing each component of an author's full name. For example, we asked the package to assign a gender to both "Debraj" and "Ray" separately. We then classified the authors as follows: if both components were assigned the same gender, we assigned that gender to the author. If there was a discrepancy across components, we identified the most popular of the components and assigned that gender to the author. We cross checked the quality of our gender assignment algorithm manually.

11.5.4 Computing citation counts of authors

We directly pulled estimated citation counts for each paper from the *Microsoft Academic Graph* (MAG) data set and from the *Crossref* dataset when the MAG information was unavailable. We then assigned to each author the sum of citations of the author's articles.

11.5.5 Assignment of institutional affiliations of authors

For a subset 47 US institutions, we matched the theorists in our sample with their home department by using a dataset a manually collectedby us. A department is included if it is in the top 50 list of the *RePEc* US department rankings in 2013, 2014 and 2015.[45] The department level dataset covered all faculty members as well as their titles from 1995 to 2019 from two sources (department websites and course catalogues). We matched our sample of theorists to the faculty members in these departments using their names. This sums up to a total of 11,087 theorists with affiliation info.

11.6 Description of the methodology to estimate the community detection model based on Feng et al. (2023)

Taking logs from (6), we can express the log likelihood compactly as

$$\log \mathcal{L} = \sum_{t\in\{\ell,c\}} n_t(\boldsymbol{\tau})\log(\pi_t) + \sum_{t,t'\in\{\ell,c\}} M_{tt'}(\boldsymbol{\tau})\log(\omega_{tt'}) - \sum_{t,t'\in\{\ell,c\}} \omega_{tt'}B_{tt'}(\boldsymbol{\tau},\boldsymbol{\gamma}) + \sum_{i=1}^{n}\sum_{j=i}^{n} q_{ij}a_{ij}\mathbf{x}'_{ij}\boldsymbol{\gamma} \tag{9}$$

[44]See https://www.rdocumentation.org/packages/genderizeR/versions/2.0.0.
[45]See https://ideas.repec.org/top/old/1505/top.usecondept.html.

where $q_{ij} = 1$ if $j \in Q(i)$,

$$n_t(\boldsymbol{\tau}) = \sum_{i=1}^{n} 1\{\tau_i = t\}$$

is the total number of type t authors under assignment $\boldsymbol{\tau}$,

$$M_{tt'}(\boldsymbol{\tau}) = \sum_{i=1}^{n} \sum_{j=i}^{n} q_{ij} a_{ij} 1\{\tau_i = t, \tau_j = t'\}$$

is the number of co-authorships between a type t and a type t' authors under assignment $\boldsymbol{\tau}$, and

$$B_{tt'}(\boldsymbol{\tau}, \boldsymbol{\gamma}) = \sum_{i=1}^{n} \sum_{j=i}^{n} q_{ij} e^{\mathbf{x}'_{ij}\boldsymbol{\gamma}} 1\{\tau_i = t, \tau_j = t'\}$$

is an aggregate of the covariate influence in co-authorship formation among type t and a type t' authors under assignment $\boldsymbol{\tau}$.

We can first take the FOC with respect to π_t and Ω. With respect to π_ℓ:

$$\begin{aligned} & n_\ell(\boldsymbol{\tau}) \frac{1}{\pi_\ell} + (n - n_\ell(\boldsymbol{\tau})) \frac{1}{1 - \pi_\ell}(-1) = 0 \\ & \Rightarrow \\ & \pi_\ell^{MLE} = \frac{n_\ell(\boldsymbol{\tau})}{n} \end{aligned} \tag{10}$$

With respect to $\omega_{tt'}$,

$$\begin{aligned} & \frac{M_{tt'}(\boldsymbol{\tau})}{\omega_{tt'}} - B_{tt'}(\boldsymbol{\tau}, \boldsymbol{\gamma}) = 0 \\ & \Rightarrow \\ & \omega_{tt'}^{MLE} = \frac{M_{tt'}(\boldsymbol{\tau})}{B_{tt'}(\boldsymbol{\tau}, \boldsymbol{\gamma})} \end{aligned} \tag{11}$$

Plugging back (10) and (11) into (9), we obtain the profile likelihood:

$$\begin{aligned} \log \mathcal{L}^* = & \sum_{t \in \{\ell, c\}} n_t(\boldsymbol{\tau}) \log \left(\frac{n_t(\boldsymbol{\tau})}{n} \right) + \sum_{t, t' \in \{\ell, c\}} M_{tt'}(\boldsymbol{\tau}) \log \left(\frac{M_{tt'}(\boldsymbol{\tau})}{B_{tt'}(\boldsymbol{\tau}, \boldsymbol{\gamma})} \right) \\ & - \sum_{t, t' \in \{\ell, c\}} \frac{M_{tt'}(\boldsymbol{\tau})}{B_{tt'}(\boldsymbol{\tau}, \boldsymbol{\gamma})} B_{tt'}(\boldsymbol{\tau}, \boldsymbol{\gamma}) + \sum_{i=1}^{n} \sum_{j=i}^{n} q_{ij} a_{ij} \mathbf{x}'_{ij} \boldsymbol{\gamma} \end{aligned}$$

Notice that the third sum is a constant equal to the total number of co-authorships, so it does not depend on $\boldsymbol{\tau}$ or $\boldsymbol{\gamma}$.

Thus, maximizing $\log \mathcal{L}^*$ is equivalent to maximizing

$$\log \tilde{\mathcal{L}}^* = \sum_{t\in\{\ell,c\}} n_t(\boldsymbol{\tau}) \log\left(\frac{n_t(\boldsymbol{\tau})}{n}\right) + \sum_{t,t'\in\{\ell,c\}} M_{tt'}(\boldsymbol{\tau}) \log\left(\frac{M_{tt'}(\boldsymbol{\tau})}{B_{tt'}(\boldsymbol{\tau},\boldsymbol{\gamma})}\right) + \sum_{i=1}^{n}\sum_{j=i}^{n} q_{ij}a_{ij}\mathbf{x}'_{ij}\boldsymbol{\gamma} \tag{12}$$

For a given ideological assignment $\tilde{\boldsymbol{\tau}}$, the terms of the form $n_t \log(n_t/n)$ and $M_{tt'} \log(M_{tt'})$ do not depend on $\boldsymbol{\gamma}$, so

$$\hat{\boldsymbol{\gamma}}(\tilde{\boldsymbol{\tau}}) = \text{argmax}_{\,\gamma} \left\{ \sum_{i=1}^{n}\sum_{j=i}^{n} q_{ij}a_{ij}\mathbf{x}'_{ij}\boldsymbol{\gamma} - \sum_{tt'\in\{\ell,c\}} M_{tt'}(\tilde{\boldsymbol{\tau}}) \log\left(B_{tt'}(\tilde{\boldsymbol{\tau}},\boldsymbol{\gamma})\right) \right\}$$

This objective function is strictly concave in $\boldsymbol{\gamma}$, so it has a unique solution that can be easily found with a BFGS algorithm.

We can now plug in $\hat{\boldsymbol{\gamma}}(\tilde{\boldsymbol{\tau}})$ in (7):

$$\log \tilde{\mathcal{L}}^*(\tilde{\boldsymbol{\tau}}) = \sum_{t\in\{\ell,c\}} n_t(\tilde{\boldsymbol{\tau}}) \log\left(\frac{n_t(\tilde{\boldsymbol{\tau}})}{n}\right) + \sum_{t,t'\in\{\ell,c\}} M_{tt'}(\tilde{\boldsymbol{\tau}}) \log\left(\frac{M_{tt'}(\tilde{\boldsymbol{\tau}})}{B_{tt'}(\tilde{\boldsymbol{\tau}},\hat{\boldsymbol{\gamma}}(\tilde{\boldsymbol{\tau}}))}\right) + \sum_{i=1}^{n}\sum_{j=i}^{n} q_{ij}a_{ij}\mathbf{x}'_{ij}\hat{\boldsymbol{\gamma}}(\tilde{\boldsymbol{\tau}}) \tag{13}$$

The space of possible vectors $\boldsymbol{\tau}$ is very large; there are 2^n possible vectors. Feng et al. (2023) propose an algorithm that works very well:

1. Pick an arbitrary $\tilde{\boldsymbol{\tau}}$, and find $\hat{\boldsymbol{\gamma}}(\tilde{\boldsymbol{\tau}})$.
2. Maximize (13) evaluated at $\hat{\boldsymbol{\gamma}}$ using an EM algorithm. For details on the EM algorithm, see Feng et al. (2023).
3. This yields an allocation $\tilde{\boldsymbol{\tau}}(\tilde{\boldsymbol{\gamma}})$.
4. Iterate if desired, although in practice the first iteration will already deliver a very accurate allocation.

11.7 Description of the methodology to estimate the multinomial choice model through simulated maximum likelihood

We maximize (8) using the method of maximum simulated likelihood. This entails numerically simulating the double integral that averages over the distribution of peer effects conditional on $\mathbf{w}_i$. We simulate this integral with a discrete sum. The estimator takes the form

$$ln\hat{L}(\boldsymbol{\gamma}) = \sum_{a=1}^{N} \sum_{\rho \in \{m,f,x,p\}} 1\{p_{a(ij)t} = \rho\} \times$$
$$ln \left[\frac{1}{B_1} \frac{1}{B_2} \sum_{b_i(\mathbf{w}_i)=1}^{B_1} \sum_{b_j(\mathbf{w}_j)=1}^{B_2} G_\rho \left(V^\rho_{a(ij)t}(b_i, b_j) \right) \right],$$

where

$$G_\rho(v^\rho) = \frac{\exp{(v^\rho)}}{1 + \sum_{s \in \{m,f,x\}} \exp{(v^s)}},$$

and the $b_k(\mathbf{w}_k)$ are draws for the β coefficients for each author from normal distributions conditional on $\mathbf{w}_k$, and B_1, B_2 are the number of draws for approximating the integrals. For single-authored papers the integral is effectively one dimensional.