Is Team Formation Gender Neutral? Evidence from Coauthorship Patterns

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We model team formation as a random matching process influenced by agents' preferences for team size and gender composition. We then test if the coauthorship pattern in articles published during 1991–2002 in three top economics journals is gender neutral, exploiting variation in female presence across subfields. Controlling for author, team, and field characteristics, we find that the gender gap in the propensity to coauthor with a woman increases in the presence of women in the subfield. We also find that women single author significantly more than men. These findings allow us to reject gender neutrality in team formation in economics.

I. Introduction

Teamwork is a feature of many professional activities. Teamwork makes specialization possible, and it also allows team members to join forces and take on projects too large for a single individual. Teamwork can

We thank Jesper Roine, Åsa Rosén, and seminar participants at Stockholm and Uppsala University, SOFI, and the Research Institute for Industrial Economics for useful comments. We are also indebted to Edda Leitner for help with the American Economic Association directories. Assistance with data coding from Jakob Eliasson, Christina Håkansson, Gulay Özcar, and David Zimmerman is gratefully acknowledged. Contact the corresponding author, Anne Boschini, at anne.boschini@ne.su.se.

[*Journal of Labor Economics,* 2007, vol. 25, no. 2]

0734-306X/2007/2502-0003$10.00

therefore improve productivity.[1] Both the gains and the costs of teamwork are linked to the heterogeneity of the team members. While the benefits of heterogeneity may depend on the nature of the activity as in Prat (2002), coordination costs are typically thought of as increasing with the heterogeneity of team members. One potentially important dimension of heterogeneity is gender. Recent experimental evidence in Ivanova-Stenzel and Kübler (2005) shows that the gender composition of teams affects team productivity, and, in particular, they find that women perform worse in gender-mixed teams.

Uncovering the influence of gender on team productivity and team formation is important for understanding the driving forces underlying gender differences in career choice and persistence in occupational gender segregation.[2] Anyone considering the hard work required to reach top management positions, or to become a professor in economics, needs to take into account the prospects of ever joining the board of directors or finding good coauthors. Whenever there is gender sorting in team formation, these prospects are smaller for the gender in minority.

The question asked in this article is whether gender plays a role in voluntary team formation. More specifically, we investigate empirically whether the authorship pattern resulting from the voluntary team formation of academic economists is neutral with regard to gender. We address this question by developing a simple model of team formation of agents who have team size and gender preferences. We then test our theoretical predictions on the authorship pattern in articles published in three top journals of economics, exploiting the variation in the presence of women across subfields of economics. Our findings suggest that gender does matter for team formation.

The main contribution of this article is to show that there is gender sorting in team formation in economics at the subfield level. By modeling team formation of agents who have preferences over gender composition and team size, we derive implications of gender neutrality for how the gender gap in the propensity to form teams with women depends on the presence of women. This allows us to rule out that the gender sorting found in the data is an artifact of gender differences in field choice or preferences for teamwork. Using information on author publication records and affiliations, we can also exclude that the gender sorting found is the result of gender differences in seniority or gender sorting at the department level. Another interesting finding is that all-female teams are

[1] Becker and Murphy (1992) show how the realization of the potential benefits of teamwork depends on the ability to coordinate the efforts of the team members. Benefits of teamwork also depend on the incentives for team members to contribute, as in, e.g., Kendal and Lazear (1992).

[2] See, e.g., Breen and García-Peñalosa (2002) for references on occupational gender segregation.

more likely to be long-distance collaborations than are gender-mixed teams. This suggests that mixed teams, compared to all-female teams, are less likely to be formed when they have to take on the extra coordination costs associated with long-distance collaboration.

We have chosen to study team formation in academia and more specifically in economics, which is one of many male-dominated academic and professional fields. There are two reasons for this choice. First, team formation in academia is voluntary. Researchers team up only when all parties think that they are better off collaborating than writing articles alone. Consequently, the teams formed are likely to reflect individual tastes and perceptions of the returns to collaboration, as well as the costs of coordination. Second, quantity and quality of output in academia are easily measured by publications in academic journals of different rank. This allows us to control for individual heterogeneity in productivity. We have limited the present study of authorship patterns to articles published in three general top economics journals, the *American Economic Review*, the *Journal of Political Economy*, and the *Quarterly Journal of Economics*, between 1991 and 2002. Apart from reducing the variation in the quality of research output, a further argument for selecting these journals is that they have been the focus of other recent studies of authorship patterns in economics, notably Laband and Tollison (2000) and Hamermesh and Oster (2002).

Ferber and Teiman (1980) and McDowell and Kiholm Smith (1992), established early on that there is a pattern of gender sorting in coauthorships in economics and that women write more single-authored articles. In data from 1969 to 1986 on the publications of a sample of 178 PhDs from the top 20 U.S. institutions, McDowell and Kiholm Smith (1992) found that women were over five times more likely than men to have female coauthors. Gender sorting as a reason for high rates of female single authorship and for the difficulties of women pursuing careers in the economics profession is discussed by Kahn (1995, 2002), McDowell, Singell, and Ziliac (1999, 2001), and Ginther and Kahn (2004).

A drawback of the earlier studies of gender sorting is that they do not rule out that gender sorting in coauthorship may result from gender sorting in the choice of subfields or that high female single authorship may be the consequence of gender differences in preferences for teamwork or of differences in single authorship across subfields. The present study, as well as Dolado, Felgueroso, and Almunia (2005), shows that there is, in fact, considerable gender segregation in the choice of subfields. We also find large variation across subfields in the prevalence of single authorship.[3]

The article proceeds as follows. In Section II, we develop a model of team formation in which researchers have preferences for team size and

[3] This is also found in Hamermesh and Oster (2002).

gender composition. We generate a set of testable predictions for how the male and female propensities to coauthor with a woman and to single author depend on the fraction of women in the population of researchers. Next, in Section III, we present our data on team formation in economics, which show recent trends in authorship patterns. We investigate whether the overall pattern in the data suggests gender sorting in team formation by comparing it to what would have been the outcome of random, gender-neutral team formation. We find that, on average, women are twice as likely as men to coauthor with women but that gender differences in single authorship are minor. We also find a fair amount of author, team, and field heterogeneity that could potentially account for the gender gap. Section IV formally tests whether the authorship pattern is the outcome of gender-neutral team formation. We estimate probit models of the probability to coauthor with a woman and the probability to single author, controlling for author, article, team, and field heterogeneity. We are able to reject that the authorship pattern in economics is consistent with gender-neutral preferences. Various robustness checks confirm the pattern of gender sorting in team formation. Section V concludes.

II. A Simple Model of Gender Preferences in Team Formation

Assume a population of equally able male and female researchers within a research field. The fraction of female researchers is exogenously given by ϕ, and the male fraction is $1 - \phi$. Researchers can work alone or do research in teams.

First, let u_{ia} be the utility accruing to a researcher of gender i of doing research in a team of type $a \in \{S, M, C\}$, where

S = single authorship;

M = mixed coauthorship, i.e., a team with the opposite sex;

C = single-sex coauthorship, i.e., a team with the same sex.

Second, let researchers rank these team types differently. We assume that the preferences over teamwork and gender are independent, but we allow for the possibility that preference distributions are gender specific. In order to focus on the issue of gender preferences, the model abstracts from team-formation considerations that stem from differences in individual research ability, which drive team-formation patterns in Goyal, Van der Leij, and Moraga-Gonzáles (2006). In the empirical analysis in Section IV below, we will, however, control for observable individual differences in research productivity.

Let a fraction μ_i of gender i always rank teamwork higher than working alone, while a fraction σ_i always prefers single work. Let the remaining $(1 - \sigma_i - \mu_i = \kappa_i)$ fraction of agents rank teamwork or single work higher

Table 1
Joint Distribution of Gender and Team-Size Preferences for Authors of Gender *i*

	Gender Preferences	
Team-Size Preferences	Gendered $(1 - \nu_i)$	Neutral (ν_i)
Single (σ_i)	$\sigma_i(1 - \nu_i)$ $[u_{iS} > u_{iU}]$	$\sigma_i \nu_i$ $[u_{iS} > u_{iU} = u_{iH}]$
Conditional (κ_i)	$\kappa_i(1 - \nu_i)$ $[u_{iH} < u_{iS} < u_{iU}]$	$\kappa_i \nu_i$ $[u_{iH} = u_{iS} = u_{iU}]$
Multi (μ_i)	$\mu_i(1 - \nu_i)$ $[u_{iS} < u_{iH}]$	μ_i $[u_{iS} < u_{iH} = u_{iU}]$

NOTE.—Data are the fraction of gender *i* of the preference type specified. The implied ranking of utility derived from working in teams of different types is in square brackets.

depending on the sex of the prospective coauthor. Further, assume that a fraction (ν_i, independent of σ_i and μ_i) of agents of gender i is neutral regarding the gender of teammates, while the remainder $(1 - \nu_i)$ has gendered preferences, that is, prefers working in single-sex teams to working in mixed teams. The joint distribution of gender and team-size preferences for gender i and the implied ranking of team types is given by table 1.

We do not model explicitly why researchers differ in their rankings over teamwork and gender, but there may be both productivity concerns and pure taste underlying these rankings. Teamwork may be more or less rewarding depending on the agent's ability to realize the potential benefits of teamwork or the effort and enjoyment associated with working in teams. A possible source of gender difference in the ranking of teamwork versus single authorship may stem from differences in responsibilities outside the workplace, which can render coordination with a coauthor more complex. As regards gender preferences, there may be real or perceived gender-specific coordination costs that affect the quality of the output or the effort required in producing it. Alternatively, as suggested in Ivanova-Stenzel and Kübler (2005), gender composition may affect team members' willingness to contribute and to free ride. Furthermore, following the advice of Hamermesh (2004) to young female economists, if a researcher suspects that she will not be duly credited for her contribution to the output produced in a mixed team, she ought not to be part of such a team.

A. Team Formation and the Distribution of Articles by Team Type

Each period, agents are randomly matched in pairs. Each pair will form a team and jointly write two articles, unless one or both agents strictly prefer working alone. In that case, they will write one paper each. Hence, output in the number of articles per person is assumed to be constant across team types and per period.[4] Given the distribution of preferences described above, we can derive the distribution of articles by team type. This matching process is mechanical in the sense that individual researchers do not act on their preference in order to affect the likelihood of finding a good match. One way to look at it is that by choosing to work within a specific field, where the distribution of preferences and gender composition are given, the individual has already maximized the likelihood of finding the preferred match. In other words, the matching process takes place within the agents' preferred field and results in a distribution of articles by team types.

The fraction of articles produced by female coauthorships is the product of the probability that two women are matched in a pair and the probability that none of them strictly prefer working alone to working with another woman:

$$P(C_f) = \phi^2(1 - \sigma_f)^2. \tag{1}$$

Analogous reasoning applies throughout. Hence, the fraction of articles produced by male coauthorships is

$$P(C_m) = (1 - \phi)^2(1 - \sigma_m)^2. \tag{2}$$

From equations (1) and (2) it is clear that the fractions of male and female coauthorships depend only on the fraction of women in the population and the preference for single authorship, σ_i. The fraction of articles produced in mixed coauthorships is given by the probability of obtaining a gender-mixed match times the probability that none of the researchers prefer writing alone, either because they have preferences for single authorship or because they do not like working with the opposite sex:

$$P(M) = 2\phi(1 - \phi)(\mu_f + \kappa_f\nu_f)(\mu_m + \kappa_m\nu_m). \tag{3}$$

Male and female single authors are all those who got matched to the same sex, where either of the two potential teammates did not want to coauthor, plus those who got teamed up with someone of the opposite sex and found that at least one of them did not want to coauthor or had preferences against the opposite sex:[5]

$$P(S_f) = \phi^2[1 - (1 - \sigma_f)^2] + \phi(1 - \phi)[1 - (\mu_f + \kappa_f\nu_f)(\mu_m + \kappa_m\nu_m)], \tag{4}$$

[4] In the economics literature, the assumption of a constant value of output per researcher across team sizes finds some support in the empirical findings of Sauer (1988) and McDowell and Kiholm Smith (1992).

[5] It is easily verified that the total share of articles attributed to female authors is indeed $\phi, P(S_f) + P(T_f) + P(M)/2 = \phi$.

and

$$P(S_m) = (1-\phi)^2[1-(1-\sigma_m)^2] + \phi(1-\phi)[1-(\mu_f+\kappa_f\nu_f)(\mu_m+\kappa_m\nu_m)]. \quad (5)$$

B. Implications for Differences in Male and Female Authorship Patterns

The next step is to investigate how male and female authorship patterns depend on the fraction of women present in the research field under different assumptions regarding the importance of gender preferences, ν_i. The propensity to coauthor with a woman, that is, the conditional probability to have a female teammate (FTM), is

$$P(FTM\mid m) = \frac{P(M)}{2(1-\phi)} = (\mu_f+\kappa_f\nu_f)(\mu_m+\kappa_m\nu_m)\phi \text{ and} \quad (6)$$

$$P(FTM\mid f) = \frac{P(C_f)}{\phi} = (1-\sigma_f)^2\phi, \quad (7)$$

for men and women, respectively.

It is clear from equations (6) and (7) that the male and female propensities to coauthor with a woman are linear and increasing in the fraction of women, ϕ. Moreover, while the male propensity to coauthor with a woman decreases with the fraction of agents of either sex who have gender-biased preferences, the female propensity to coauthor with a woman is independent of gender preferences since, by assumption, there are no agents who have a preference against their own gender.

We now turn to the propensities to single author. These can be written as

$$P(S\mid m) = \frac{P(S_m)}{1-\phi} = \sigma_m(2-\sigma_m) + [(1-\sigma_m)^2 - (\mu_f+\kappa_f\nu_f)(\mu_m+\kappa_m\nu_m)]\phi; \quad (8)$$

$$P(S\mid f) = \frac{P(S_f)}{\phi} = [1-(\mu_f+\kappa_f\nu_f)(\mu_m+\kappa_m\nu_m)] + [(\mu_f+\kappa_f\nu_f)(\mu_m+\kappa_m\nu_m)-(1-\sigma_f)^2]\phi. \quad (9)$$

Also, the propensities to single author are linear in the presence of women, ϕ. Expressions (6)–(9) can therefore be summarized as follows:

$$P(FTM\mid i) = \beta_i^{FTM}\phi, \text{ and}$$

$$P(S\mid i) = \alpha_i + \beta_i^S\phi,$$

where β_i^{FTM}, α_i, and β_i^S depend on the parameters of the model.

Next, we analyze the implications of alternative hypotheses regarding the distributions of preferences of male and female researchers for equations (6)–(9). We formulate two hypotheses: (i) gender irrelevance and (ii) gender neutrality. The first states that gender is irrelevant and that there is one population of gender-neutral agents who are all drawn from the same distribution of team-size preferences. The second hypothesis is less strong in the sense that there may be systematic gender differences in team-size preferences, even if gender preferences per se are neutral.

Proposition 1 (gender irrelevance). If $\sigma_f = \sigma_m = \sigma$, $\mu_f = \mu_m = \mu$, and $\nu_f = \nu_m = 1$, gender is irrelevant for team formation and $\beta_f^{FTM} = \beta_m^{FTM}$, $\alpha_f = \alpha_m$, and $\beta_f^S = \beta_m^S = 0$.

Proof. See appendix A.

When researchers are gender neutral and male and female researchers share the same team preferences, gender is irrelevant for the authorship pattern. Hence, single authorship is obviously the same for men and women and insensitive to the fraction of female researchers. The propensity to form a team with a woman will also be the same for men and women: there is no gender gap.

Proposition 2 (gender neutrality). If $\sigma_f \neq \sigma_m$ and $\nu_f = \nu_m = 1$, then $\sigma_m \gtreqless \sigma_f$ implies that $\beta_m^{FTM} \lesseqgtr \beta_f^{FTM}$, $\alpha_m \gtreqless \alpha_f$, and $\beta_m^S \lesseqgtr \beta_f^S$.

Proof. See appendix A.

Allowing for gender differences in team preferences, our model suggests that the qualitative implications of gender neutrality hinge on which gender has the strongest preference for single authorship, that is, whether $\alpha_m \gtreqless \alpha_f$. It is also clear that it is possible to have gender neutrality even when there is a gender gap in the propensity to coauthor with a woman. In particular if, as was found in previous empirical studies, female researchers have a higher propensity to coauthor with women than with men, then $\beta_f^{FTM} > \beta_m^{FTM}$. Proposition 2 shows that preferences still can be gender neutral if male researchers single author more often than female researchers do.[6] This result is illustrated in figure 1, which plots expressions (6)–(9). The graph in figure 1 shows how the fraction of women, ϕ, on the x-axis, affects the male and female propensities to single author and to coauthor with a woman under the assumptions that preferences are gender neutral, that is, $\nu_f = \nu_m = 1$, and the fraction of male researchers who prefer to work alone is larger than the fraction of female researchers who prefer single work, $\sigma_m > \sigma_f$.[7] The graph shows that as the fraction of women, ϕ, increases, the female propensity to coauthor with a woman,

[6] Recall, however, that Ferber and Teiman (1980) and McDowell and Kiholm Smith (1992) found that women wrote more single-authored papers.

[7] The parameter values used in fig. 1 are $\sigma_f = 0.1$ and $\sigma_m = 0.3$. As long as preferences are gender neutral, μ_f and μ_m are irrelevant.

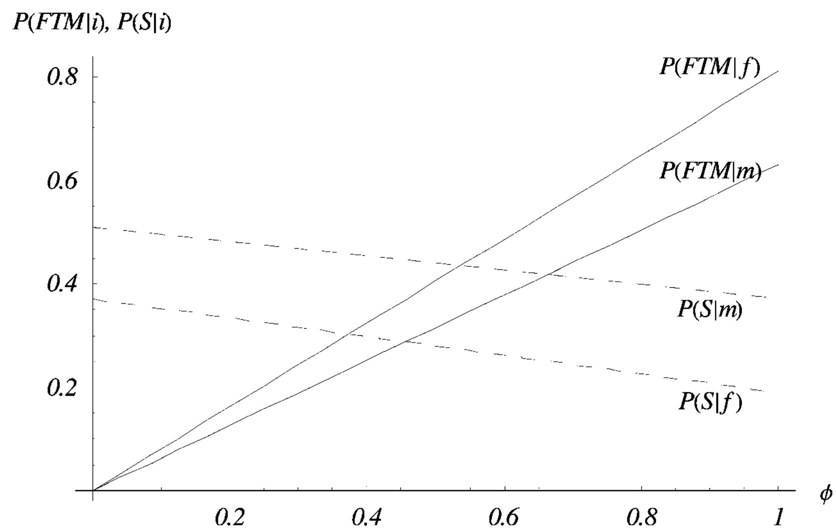

FIG. 1.—Male and female propensities to single author, $P(S|i)$, and to have a female coauthor, $P(FTM|i)$, as functions of the fraction of women, ϕ, when preferences are gender neutral, $\nu_m = \nu_f = 1$, but men have a stronger preference for single authorship, $\sigma_m > \sigma_f$.

$P(FTM|f)$, is higher and increases more rapidly than the male propensity to coauthor with a woman, $P(FTM|m)$. Hence, if gender preferences are neutral but men have a stronger preference for single authorship, there is a gender gap in the propensity to coauthor with a woman, $P(FTM|f)/P(FTM|m) > 1$, which grows with the fraction of women. Note that both the male and the female propensities to single author decline with the fraction of women, but the male propensity to single author is higher than that of female researchers.

III. Team Formation in Economics

This section presents data on the authorship pattern in articles published in the *American Economic Review* (*AER*), the *Journal of Political Economy* (*JPE*), and the *Quarterly Journal of Economics* (*QJE*), as well as data on the size and the presence of women in the different subfields of economics for 1991–2002. The data are collected from three different sources, EconLit, JSTOR, and the American Economic Association (AEA) membership directories. We report trends in team formation in relation to the findings of the previous literature. In particular, we focus on gender sorting.

A. The Data

The data set covers the 4,040 articles published in *AER*, *JPE*, and *QJE* from 1991 to 2002 and is collected mainly from EconLit.[8] The *AER* has by far the most entries and accounts for almost two-thirds of all articles. There are no significant differences among the journals, except that *AER* published shorter articles on average than the other two journals.[9] We have gender coded all the authors of each article. Excluding the 50 articles where we were unable to identify the sex of at least one of the contributing authors, we have a data set consisting of 3,090 articles written by 5,308 authors in total. Our data set, which will be referred to as the Top 3 journal's data set (T3), contains the gender and affiliation of authors, as well as JEL codes and the number of pages, print year, and source (journal) of each article.

In order to investigate how the authorship pattern depends on the fraction of women in the relevant pool of prospective collaborators, we make use of the JEL codes provided by EconLit to classify the articles into major fields. The idea is that authors writing in a particular field belong to the same subpopulation of economists. However, articles typically have more than one JEL code and, hence, belong to more than one field. We count an article with two JEL codes in both fields. The average number of JEL codes per article is 1.44. The nine most frequent JEL codes each account for more than 5% of the articles in every year of our sample period.[10]

For these nine major fields we have constructed a measure of the fraction of women in the field by computing the fraction of articles contributed by female authors. We have also computed a measure of the relative field size. In order to obtain an independent measure of the relative sizes of JEL fields, our T3 data set is complemented with JEL-code information from all the journal articles available in EconLit each year of our sample

[8] For 2002, the last numbers of *AER*, *JPE*, and *QJE* are not in the sample. 1991 is the first year in our sample due to the reform of the *Journal of Economic Literature* (JEL) classification that occurred that year. To avoid misclassifications we have not attempted to recode the JEL classifications for articles published in 1990 and earlier.

[9] One reason is that *AER* has more text per page, another is that articles in the *AER* May number (*Papers and Proceedings* of the AEA meetings) are shorter than average. We control for this in various ways in the econometric analysis of Sec. IV.

[10] The nine most frequent JEL codes are Microeconomics (D), Macroeconomics and Monetary Economics (E), International Economics (F), Financial Economics (G), Public Economics (H), Health, Education, and Welfare (I), Labor and Demographic Economics (J), Industrial Organization (L), and Economic Development, Technological Change, and Growth (O). In no single year do any of the other JEL fields rank higher than these top nine. For a complete list of JEL fields, see app. C.

Table 2
Descriptive Statistics for the Major JEL Codes (%)

	Relative Field Size		Female Share of Researchers, ϕ		Single Authorships
JEL Code	Our Sample of Articles	EconLit Articles	Our Sample of Researchers	AEA Members	Our Sample of Authorships
D–Microeconomics	19.4	7.3	9.6	12.9	41.0
E–Macroeconomics and Monetary Economics	11.2	6.0	7.5	9.3	42.4
F–International Economics	7.5	6.5	11.6	13.5	47.2
G–Financial Economics	7.4	6.9	9.5	9.0	27.4
H–Public Economics	6.7	3.6	10.0	13.1	42.7
I–Health, Education, and Welfare	5.8	3.4	21.4	23.1	44.2
J–Labor and Demographic Economics	15.7	6.5	19.4	20.6	41.3
L–Industrial Organization	8.3	6.8	14.1	12.6	36.8
O–Economic Development, Technological Change, and Growth	10.1	8.2	12.0	12.2	41.2
Other	8.0	46.1	12.8	11.4	54.2
All	100.0	100.0	12.6	15.7	41.7

Note.—Information from the Top 3 journals, *AER*, *JPE*, and *QJE* (T3), compared to EconLit and the AEA membership directories. Columns 1 and 2 do not sum to 100 due to rounding errors.

period. Since authors in EconLit are not gender coded, we have used the AEA membership directories for 1993, 1997, and 2002 to construct independent measures of the fraction of female researchers in each major JEL field. (See apps. C and D for detailed descriptions of the data from EconLit and the AEA directories.) We believe the AEA directories are reasonably representative of the population of researchers publishing in these top journals. First, a very large fraction of the authors in our sample are affiliated with American universities, and second, many of the researchers affiliated with non-American institutions who publish in top journals are members of the AEA. Table 2 summarizes the information on the fraction of women and the relative size of the major JEL fields from the different data sources. Note that the major fields are relatively overrepresented in our sample, compared to all journals in EconLit. Note also that the shares of female researchers by field obtained from the AEA directories are very similar in magnitude to the shares computed from our T3 sample.[11]

EconLit does not provide any author information other than affiliation at the time of publication. In order to rule out that any gender sorting in coauthorship patterns detected in our data is due to differences in

[11] When computing these figures for the T3 data set, male and female appearances in the data have been weighted by the number of contributing authors of each article.

productivity and seniority, we have independently collected data on the publication records of all the authors in our T3 sample. Using JSTOR we have counted each author's number of publications in the top five journals (Top 5) between 1950 and the year of publication in our sample, as well as noted the year of the author's first Top 5 publication.[12]

With a total of 5,308 authors of 3,090 articles, the average team size in our data is 1.72 authors. There are 2,909 individual researchers in our sample. Two-thirds of authors appear only once in our data, and only 5% of the authors have more than five publications. Hence, it is fair to say that the publication pattern in our data is not driven by the behavior of a small number of very successful economists but rather by authors that appear at most twice.

B. Authorship Patterns in Economics

During 1991–2002, women contributed on average 13% of the articles in the Top 3 journals.[13] Table 3 reports the distribution of articles by team size and gender of the first author of the article. It is worth noting that there is no time trend in the overall contribution of women. Women account for the same fraction of articles in the first and second half of the sample period. The female contribution of 13% can be compared to a female share of faculty of 15% at U.S. PhD-granting departments in 2000, according to the annual reports of the American Economic Association Committee on the Status of Women in the Economics Profession.[14] Another striking feature is that there are only minor gender differences in the overall pattern of authorship. Table 3 reports that for the period as a whole, women, compared to men, are slightly underrepresented in coauthorships with more than two (i.e., multiple) authors (10.3% vs. 13.3%). The data also reveal that there is a decline in single authorship, in particular for women. Toward the latter half of our period of study, single authorship of men is slightly, although insignificantly, higher than that of women, such that over the period as a whole, there are only minor gender differences.

Table 3 confirms the increasing trend in coauthorships observed by others. For example, Hamermesh and Oster (2002) report an average share of coauthored articles of only 30% during the 1970s in *AER*, *JPE*, and

[12] Top 5 journals include *AER*, *JPE*, *QJE*, *Econometrica*, and the *Review of Economic Studies*. The reason for widening the sample of journals is to get as good a measure as possible of the author's top-quality publication record.

[13] Of the 3,090 articles, 12.9% have female first authors. If all 5,308 authors are considered, 11.8% are women. If the contribution of women to each article is weighted by the number of authors, as in table 2, the female share is 12.6%.

[14] Excluding untenured faculty, the figure drops to 10%, which is still a doubling since 1976. Restricting the sample to the top 20 departments puts the female share in 2000 at 8% (tenured faculty) and 13% (untenured included).

Table 3
Distribution of Articles by Team Size and Gender of First Author for Articles Published in *AER*, *JPE*, and *QJE*

	1991–96 Gender of First Author			1997–2002 Gender of First Author			1991–2002 Gender of First Author		
Team Size	Female	Male	All Articles	Female	Male	All Articles	Female	Male	All Articles
Single author	111	676	787	66	493	559	177	1,169	1,346
Row %	14.1	85.9	100.0	11.8	88.2	100.0	13.2	86.9	100.0
Column %	52.9	47.5*	48.2	35.1	38.9	38.4	44.5	43.4	43.6
Two authors	82	596	678	98	570	668	180	1,166	1,346
Row %	12.1	87.9	100.0	14.7	85.3	100.0	13.4	86.6	100.0
Column %	39.1	41.9	41.5	52.1	44.9**	45.9	45.2	43.3	43.6
Multiple authors	17	151	168	24	206	230	41	357	398
Row %	10.1	89.9	100.0	10.4	89.6	100.0	10.3	89.7	100.0
Column %	8.1	10.6	10.3	12.8	16.2	15.8	10.3	13.3*	12.8
All articles	210	1,423	1,633	188	1,269	1,457	398	2,692	3,090
Row %	12.9	87.1	100.0	12.9	87.1	100.0	12.9	87.1	100.0
Column %	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

* Significantly different (one-sided *t*-test) from corresponding female fraction at the 90% level.
** Significantly different (one-sided *t*-test) from corresponding female fraction at the 95% level.

QJE. Table 3 shows that coauthored articles make up 56.4% of the articles in the same journals between 1991 and 2002.[15]

What authorship pattern would result from random pairing and gender-neutral team formation when the fraction of female researchers is 13%? If we make the thought experiment that the authors in our sample had been randomly paired, that no author paid attention to gender, and that the male and female preferences for single authorship were the same and such that 43.6% of all authors ended up writing articles on their own, what fraction of authors would have female coauthors?[16] Simulations show that if pairing were random, we would expect to find that about 7% of all male and female authors had a female coauthor.[17] If, instead, the slight gender difference in single authorship present in the data, 43.4% for men versus 44.5 for women according to table 3, is assumed to reflect a tiny difference in male and female preferences for single authorship, a random pairing of authors would imply that the fraction of men who had a female coauthor would be slightly higher than the fraction of women who had a female coauthor.[18]

In reality, our data show that women are more than twice as likely as men to have a female coauthor. Of the male authors in our sample, 7% have at least one female coauthor. The corresponding figure for women is 16%.[19] In a study of coauthorship patterns during the 1980s, McDowell and Kiholm Smith (1992) found that women were five times more likely than men to have a female coauthor. Although the gender gap in the propensity to coauthor with a woman is nowhere near as large as during the 1980s, there still is a gap. Yet, it is too early to conclude that the gender gap in the propensity to coauthor with a woman is a result of gender preferences. It is possible that the apparent gender sorting in coauthorships is a consequence of male and female sorting into different fields of economics, or of author heterogeneity, rather than a consequence of biased gender preferences.

First, we look at the pattern across subfields. Table 2 in the previous subsection revealed large differences in the presence of women across

[15] The figure sums the fractions of articles written by two or more authors (difference due to rounding).

[16] Ignore that researchers sometimes form teams with more than two authors.

[17] If a random pair of two authors decides not to form a team, it is because at least one of them prefers writing alone. A level of single authorship of 43.6% implies that 24.9% of all authors prefer to write alone. The probability that a team is formed is $(1 - 0.249)^2 = 0.564$.

[18] Both the male and the female fractions would still be very close to 7%.

[19] In a *t*-test, the gender difference in the propensity to coauthor with a woman is statistically significant at the 99% level. Figure 2 shows the gender gap in the propensity to coauthor with a woman at the subfield level. Averaging over fields and weighting by field size reveals that 7% of men and 16% of women in the sample have at least one female coauthor.

fields. Female presence is roughly three times higher in Health, Education, and Welfare than in Macroeconomics and Monetary Economics. There are also large differences in the prevalence of single authorship across fields of economics. While only 27.4% of the Financial Economics articles are single authored, almost half of the International Economics articles have only one author. In the minor fields that constitute the Other category, as many as 54.2% of all articles are single authored. These variations across fields are likely to reflect field differences in the costs and benefits of teamwork. In the case of minor fields, the reason for single authorship may also be the result of the difficulty of finding suitable coauthors in a smaller population.[20]

How does the gender gap in the propensity to coauthor with a woman relate to the presence of women economists in a field? In figure 2, we have plotted field-specific male and female propensities to coauthor with a woman (y-axis) against the fraction of women in each field (x-axis). We have also fitted a male and a female trend line. Figure 2 reveals that the higher the share of female researchers in a field, the larger the difference between female and male coauthorship patterns. As the fraction of female researchers increases, women increasingly tend to write with other women. Also, the male propensity to coauthor with a woman is higher in fields with more women, but it increases less than that of women. Averaging across fields and weighting by field size, the overall gender gap in the propensity to coauthor with a woman is two.

This first look at the data suggests that gender is not irrelevant: there is indeed a gender gap. But the gender gap could still be the result of differences in the prevalence of single authorship across fields. Figure 3, however, shows that the levels of both male and female single authorship is uncorrelated with the presence of female researchers. It is also worth noting that only in Health, Education, and Welfare and Public Economics do women single author less than men.

A comparison of figures 2 and 3 to figure 1, which was generated by the model, does not suggest that the authorship pattern in economics is the outcome of gender-neutral team formation. However, there is still a possibility that team formation is gender neutral. This would be the case if the heterogeneity of articles, authors, and teams can account for the gender gap and for the high fraction of female single authorship. Articles, authors, and teams in our sample are heterogeneous for a number of reasons. Although our narrow choice of journals controls to some extent for quality, some articles in our sample are part of conference volumes, and some are from the AEA *Papers and Proceedings*. Furthermore, authors

[20] Mathematical and Quantitative Methods (C), Law and Economics (K), and Economic Systems (P) are examples of minor fields that account for less than 5% of the articles in our sample in any single year.

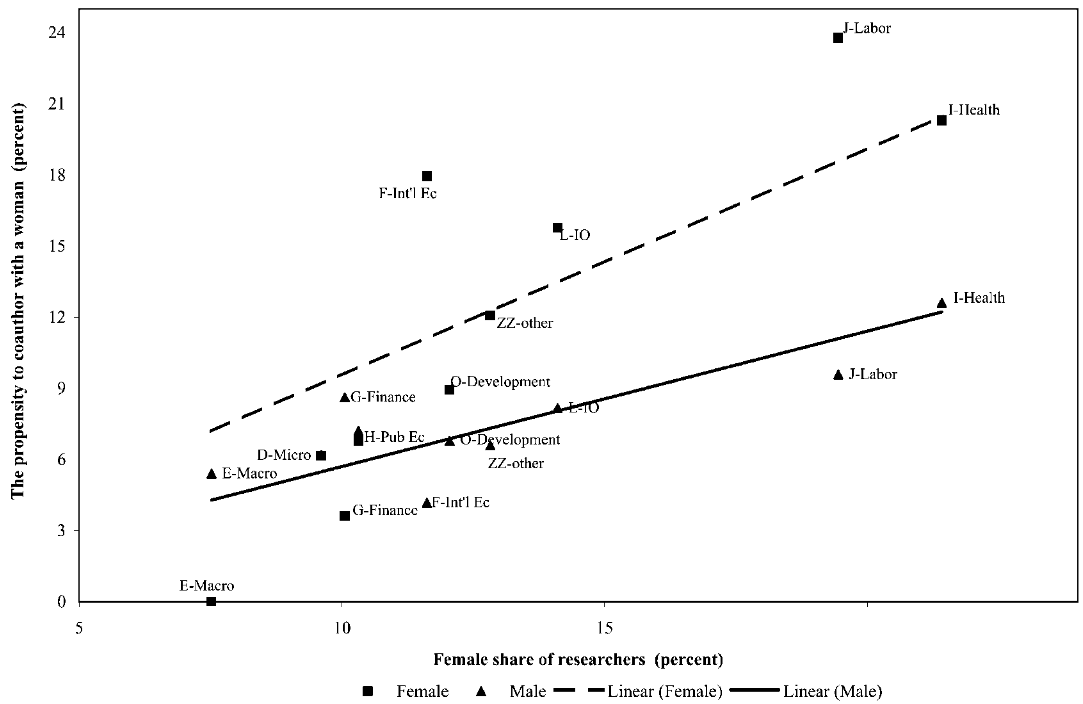

Fig. 2.—Scatter plot of the male and female propensities to coauthor with a woman against the fraction of female researchers, by JEL field (including linear trend lines). Averages for all articles published in *AER*, *JPE*, and *QJE* between 1991 and 2002.

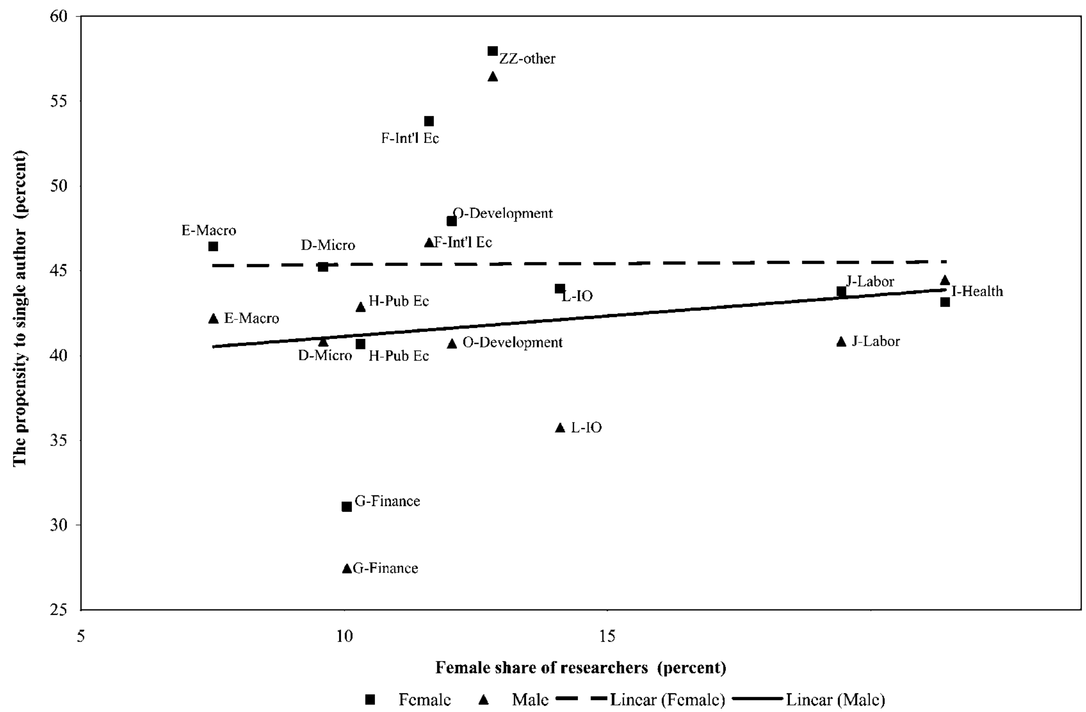

Fig. 3.—Scatter plot of the male and female propensities to single author against the fraction of female researchers, by JEL field (including linear trend lines). Averages for all articles published in *AER*, *JPE*, and *QJE* between 1991 and 2002.

Table 4
Distribution of Authors by Rank of Their Affiliation and Gender for Articles Published in *AER*, *JPE*, and *QJE* between 1991 and 2002

Rank of Author's Affiliation	Gender of Author		
	Female	Male	All Authors
Top 3 institution	68	833	901
Row %	7.6*	92.4	100.0
Column %	10.8	17.8	17.0
Top 4–20 institution	189	1,356	1,545
Row %	12.2	87.8	100.0
Column %	30.1	29.0	29.1
Other	371	2,491	2,862
Row %	13.0	87.0	100.0
Column %	59.1	53.2	53.9
All affiliations	628	4,680	5,308
Row %	11.8	88.2	100.0
Column %	100.0	100.0	100.0

NOTE.—Top 3 includes Harvard University, MIT, and the University of Chicago; Top 4–20 includes Boston University; Columbia University; Duke University; the Federal Reserve System; New York University; Northwestern University; Princeton University; Stanford University; University of California, Berkeley; University of California, Davis; University of California, Los Angeles; University of California, San Diego; University of Michigan; University of Pennsylvania; University of Rochester; University of Wisconsin; and Yale University.
* Significantly different compared to lower-ranked affiliations at the 99% level.

differ in seniority and publication record, and they are affiliated with very different institutions. Some authors always write with the same coauthors, some teams are local, and others are long distance. We cannot rule out that the gender sorting in our data is a result of systematic gender differences in any of these dimensions. Before turning to formal testing of gender neutrality, we will take a closer look at some of these potential sources of gender sorting.

C. Other Potential Sources of Gender Sorting

According to Kahn (1995), authors' affiliation is the most important determinant of differences in men's and women's publication records. The researchers in our data are affiliated with 459 different institutions. If we rank the affiliations by how often they appear in our data, half of the 5,308 authors are affiliated with the top 20 institutions, and one-fifth, with the top three, namely, Harvard University, MIT, and the University of Chicago. Table 4 shows that women are underrepresented at the top, compared to their overall representation. It is, hence, possible that some of the gender sorting in coauthorships is due to the absence of women at some of the top-ranked departments, rather than to gender preferences per se.

Another possible reason for the apparent gender sorting may be that men and women differ with regard to age and seniority, particularly if authors prefer to team up with coauthors of a similar age and publication

Table 5
Gender Differences in Publications for Different Cohorts of Authors, as Defined by the Year of the Author's First Publication in a Top 5 Journal

Cohort of Authors: Year of First Publication in a Top 5 Journal	Female Share of Authors (%)	Average No. of Publications in Top 5 Journals, 1991–2002		Gender Gap (Female Publications/ Male Publications)
		Female Authors	Male Authors	
1950–80	4.4	6.00	12.30	.49
1981–90	9.2	3.31	6.14	.54
1991–96	16.5	1.48	2.22	.67
1997–2002	19.8	1.26	1.28	.98

record. On average, the female authors in our sample have published four articles less than the men.[21] The female authors are also younger, at least as measured by the year of their first publication in Top 5 journals, which is on average 6 years more recent than for the men. It is notable that these gaps do not decline over time. If anything, the gender gaps in number of publications and year of first publication grow over our period of analysis, largely because the male authors grow older and accumulate more publications.[22] Table 5 shows the fraction of female authors and the ratio of the female-to-male publication record, given the year of the author's first Top 5 publication. For the most recent cohorts, who got their first Top 5 publications between 1997 and 2002, women make up 20% of the new authors, and the publication gap is virtually zero. In the earlier cohorts, there are fewer women, and the publication gap is wider, the further back we go.

Since the gender gap is almost closed for the most recent cohorts of economists, it is possible that gender differences in publications is a passing phenomenon. It could, however, be the case that women economists are as successful as men in publishing their dissertations but that they subsequently leave academia or become less productive than men later on in their careers. Taking a closer look at the gender gap in publications of the cohort of authors who published their first Top 5 article during 1991–96 by splitting the time period 1991–2002 into two 5-year periods reveals that the gender gap widens over time for an individual cohort. While the average publication ratio for 1991–2002 was 0.67, the ratio of female-to-male publications was 0.83 for the period 1991–96, but only 0.34 for the subsequent 5-year period. This suggests that women are

[21] This result is driven by the fact that 5% of the authors having at least five publications each are almost exclusively men and that they on average have 13 publications. The maximum number of publications by a single author is 65.

[22] There is no clear time trend in these seniority measures for female authors.

almost as successful as men early on in their careers, but they do not keep up.

Another aspect of concern is that of local versus long-distance coauthoring. As shown in Hamermesh and Oster (2002), there has been an increase in long-distance coauthorships. The Internet, they argue, has reduced the coordination costs associated with long-distance teamwork. Hence, although nearby colleagues make up the most relevant pool of potential coauthors, geography is less restrictive now than it used to be. In our data, local teams account for 20% of all articles, but it is worth pointing out that gender-mixed coauthorships are significantly underrepresented among the long-distance teams. Not surprising, given the small fraction of women at each department, all-female coauthorships tend to be less local than all-male coauthorships.[23]

As discussed in Section III.A, one-fifth of the authors in our sample are part of team constellations that appear more than once in our data. There is no statistically significant difference between all-female and all-male coauthorships in this respect, but it is interesting to note that gender-mixed teams are significantly underrepresented among the recurrent teams.

IV. Testing Gender Neutrality

In the previous section, we found a gender gap in the propensity to have a female coauthor. We also found that the prevalence of single authorship was very similar for men and women. Our model, as well as simulations, showed that such a pattern is not easily reconciled with gender-neutral team formation.[24] However, the data presented in the previous section also revealed large differences in the female presence across fields of economics. Moreover, there were clear gender differences in the rank of authors' affiliations, in publication records and in team characteristics. In this section, we estimate a more formal econometric model in which we test whether the pattern of authorship in articles published in *AER*, *JPE*, and *QJE* between 1991 and 2002 could be the outcome of gender-neutral team formation at the field level when we account for author, team, and field heterogeneity.

We estimate the following two equations. The first equation is the

[23] Female coauthorships are 73.7% local versus 67.7% of male coauthorships. This difference is not statistically significant: a t-test of the difference yields $P > |t| = 0.126$.

[24] Remember that a precondition for gender neutrality to hold in the presence of differential rates of coauthoring with women in the direction that was found is that the preference for single authorship is higher for men than for women.

probability that author i of an article in field j coauthors with a woman:

$$P(FTM)_{ij} = \alpha_1^{FTM} + \alpha_2^{FTM} f_i + \beta_2^{FTM}\phi_j + \beta_3^{FTM} f_i \phi_j + X'_{ij}\gamma + \varepsilon_i, \qquad (10)$$

where FTM stands for female teammate, f_i is an indicator variable taking the value one if author i is female, ϕ_j is the fraction of women in field j, and X is a vector of author, article, team, and field controls. The second equation specifies the probability of single authorship, S, of author i in field j and contains the same main explanatory variables as equation (10) with minor differences regarding the set of controls, Z:

$$P(S)_{ij} = \alpha_1^S + \alpha_2^S f_i + \beta_3^S \phi_j + \beta_4^S f_i \phi_j + Z'_{ij}\xi + \epsilon_i. \qquad (11)$$

The sets of control variables, X and Z, attempt to capture the various dimensions of heterogeneity in our sample. Author-specific controls capture individual characteristics of the author, such as publication record and academic affiliation. Team-specific controls capture aspects of the team, that is, if the team is local, recurrent, or both, as well as differences in seniority among the team members. Field-specific controls aim at capturing technological differences across fields, for example, prevalence of single authorship. Article-specific controls include dummy variables for the different journals, year of publication, and number of pages. We allow for several interaction effects between the control variables and the variable *female*, in order to capture any potential gender differences in these other dimensions of the sample.

In equations (10) and (11), the key coefficients of interest are β_3^{FTM}, α_2^S, and β_4^S. If gender is irrelevant, that is, authors are gender neutral and there are no gender differences in preferences for single authorship, we would expect these coefficients to be zero. If we find that there is a gender gap in the propensity to coauthor with a woman, that is, $\beta_3^{FTM} > 0$, then when we control for author and field heterogeneity, we can reject gender neutrality only if we also find that $\alpha_2^S < 0$ and $\beta_4^S > 0$.

A. Variable Construction

We treat the 3,090 articles in our sample as independent observations. The characteristics of the first author of the article are used as author-specific controls. Hence, we use the alphabet and family names as the randomizing device that draws the first author as a "representative" author of the article.[25]

The dependent variable of equation (10) is the binary variable FTM. It takes the value one if at least one of the coauthors (first author excluded)

[25] In Sec. IV.C, we present results when all 5,308 authors are included as observations. Since the qualitative results are not altered, we will focus the presentation on the specification using articles as observations.

of the article in question is a woman, and zero otherwise. Hence, if the first author is female, the article needs to have a minimum of two female authors.[26] In the second equation (eq. [11]), the dependent variable takes the value one if the article is single authored, and zero otherwise. In what follows, all variables included in the analysis are presented. Full definitions and sources are provided in appendix E, and summary statistics are reported in table B1 in appendix B.

There are three author-specific variables, *female*, *publications in Top 5*, and *affiliation to Top 3*. *Female* takes the value one if the first author is a woman, and zero otherwise. *Publications in Top 5* is the publication record in Top 5 journals between 1950 and the year of publication for the first author of the article. *Affiliation to Top 3* is an indicator variable taking the value one if the first author is affiliated with the University of Chicago, Harvard University, or MIT.

As a measure of our main explanatory variable, namely, the fraction of women in the relevant population of researchers, corresponding to ϕ in the model, we compute an article-specific *mean female share*. Since articles typically have more than one JEL code, we define the *mean female share* of the article as the weighted average of the female share in the JEL fields of the article in the publication year, where the weights are the relative sizes of the JEL fields in that year. The female share by JEL field is computed as the share of female-to-male authors of all the articles in the JEL field, weighted by the number of authors of each article. The average female share of articles in each JEL field and the sizes of fields over time are reported in table 2 above. The construction of the article-specific measure of the prevalence of single authorship, *mean single share*, is analogous.

In addition to the measures of the *mean female share* and the *mean single share* constructed with data from our sample (T3), we use the AEA membership directories for 1993, 1997, and 2002 as an independent source for the female share in the JEL fields and the entire EconLit as a source for the relative sizes of subfields in economics.[27] Using these alternative

[26] The dependent variable takes the value zero for all single-authored articles.

[27] Linear extrapolation of the female shares by JEL field for 1993, 1997, and 2002 has been used to obtain yearly field-specific female shares. The AEA membership directory has no good measure of the size of JEL fields over time. The AEA directories contain information about the members' two main fields of research. There appears, however, to be a strong trend in how members indicate their research interest since the beginning of the 1990s. For example, Macroeconomics and Monetary Economics (E) and International Economics (F) accounted for approximately 40% of members' research interests in 1993 but only accounted for 20% in 1997. These trends do not correspond to the development either in our sample or in the sample of all articles in EconLit. Thus, it is most likely due to a changing norm within the profession going from indicating general research interests to more specific JEL fields.

sources of information of the female share by field (i) and field size (j), we construct four different measures of the *mean female share (ij)*. These are *mean female share (T3T3)*, *mean female share (T3EconLit)*, *mean female share (AEAT3)*, and *mean female share (AEAEconLit)*. For the *mean single share (ij)*, we only have information on the share of single-authored articles (i) from our sample. Hence, we have *mean single share (T3T3)* and *mean single share (T3EconLit)*.

There are two team-specific indicator variables included in the main analysis. The first, *local team*, takes the value one if at least one of the coauthors has the same affiliation as the first author, and zero otherwise. The second, *senior*, takes the value one if the first author has a better publication record than the coauthors.

As article-specific variables we use *print year* to control for time trends, *source* to capture potential differences among our three journals, and the *number of pages* of the article as a potential indicator of quality. We also include dummy variables for the *AER Papers and Proceedings* and for conference volumes in the *JPE*.

B. Main Results

Table 6 reports the log-odds estimates from the probit estimation of equation (10) when only articles with two authors are included.[28] The dependent variable is FTM. The advantage of using only observations with two authors is that FTM is then a truly binary variable. The loss of observations is relatively minor since only one-fifth of the non-single-authored articles have more than two authors.[29] All estimations include all the article-specific controls, the article's mean single share, and dummy variables for each JEL field. The parameter estimates are not reported due to space limitations.

Column 1 in table 6 contains only two explanatory variables (the nonreported controls uncounted), *female* and *mean female share*. None of these are significant, indicating that on average women are not more likely to have a female coauthor than men are. When the interaction between *female* and *mean female share* is included, the results change. The interaction effect is now positive and significant at the 99% level. Thus, as the *mean female share* increases, the female propensity to coauthor with a woman increases significantly more than the male propensity to coauthor with a woman. The interaction effect remains highly significant when including additional controls and also when changing the

[28] Logit estimations yield very similar results and are available from the authors upon request.

[29] Including all observations while controlling for multiple authorship leaves the results qualitatively unchanged, as is shown in the robustness checks in Sec. IV.C.

Table 6
Probit Estimation Results with Female Teammate as the Dependent Variable

	Probability of Having a Female Teammate (*FTM*)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Characteristic of the first author:									
Female	73.571	31.838	19.766	10.498	8.832	6.691	74.749	3.432	73.533
	(69.216)	(71.140)	(72.012)	(71.757)	(72.181)	(73.138)	(74.382)	(73.404)	(74.383)
Publications in Top 5				.007	.011	−.003	−.002	−.003	−.002
				(.008)	(.008)	(.010)	(.010)	(.010)	(.010)
Female × publications in Top 5				−.036	−.025	−.065	−.073*	−.066	−.074*
				(.033)	(.033)	(.042)	(.043)	(.042)	(.043)
Affiliation to Top 3					−.377**	−.387**	−.393**	−.388**	−.394**
					(.167)	(.163)	(.163)	(.163)	(.163)
Female × affiliation to Top 3					−.028	.014	.005	.060	.041
					(.368)	(.371)	(.365)	(.368)	(.363)
Characteristic of the field(s):[a]									
Mean female share (T3T3)	4.045	.578	−.282	−.115	−.230	−1.322			
	(3.556)	(3.836)	(3.907)	(3.885)	(3.867)	(3.853)			
Female × mean female share (T3T3)		10.444***	11.026***	10.970***	10.572***	10.755***			
		(3.041)	(3.085)	(3.107)	(3.125)	(3.174)			
Mean female share (T3EconLit)								−.199	
								(3.512)	
Female × mean female share (T3EconLit)								11.090***	
								(3.258)	

Mean female share (AEAT3)							.469		
							(2.782)		
Female × mean female share (AEAT3)							6.587**		
							(2.855)		
Mean female share (AEAEconLit)									1.068
									(2.756)
Female × mean female share (AEAEconLit)									6.882**
									(2.863)
Characteristic of the team:									
Local team			.101	.101	.100	.109	.104	.111	.107
			(.113)	(.113)	(.113)	(.115)	(.115)	(.115)	(.115)
Female × local team			−.819***	−.801***	−.836***	−.817***	−.806***	−.791***	−.790***
			(.266)	(.268)	(.265)	(.271)	(.267)	(.269)	(.266)
Senior						.473***	.468***	.473***	.469***
						(.118)	(.119)	(.119)	(.119)
Female × senior						.160	.190	.161	.196
						(.300)	(.299)	(.299)	(.300)
Pseudo R^2	.0661	.0772	.0882	.0900	.0973	.1188	.1140	.1192	.1149

Note.—Sample consists only of articles with exactly two coauthors; robust standard errors are in parentheses; constant is not reported; $N = 1{,}346$.

[a] Data source for female share, *i*, and field size, *j*, is in parentheses (*ij*), where the sources for *i* and *j* are T3 = *AER*, *JPE*, and *QJE*, 1991–2002; EconLit = all articles in EconLit, 1991–2002; and AEA = American Economic Association membership directories, 1993, 1997, and 2002.

* Significant at the 90% level.

** Significant at the 95% level.

*** Significant at the 99% level.

data sources of the *mean female share* (see cols. 7–9 in table 6). The probability of coauthoring with a woman is significantly lower for authors affiliated with Harvard, MIT, or the University of Chicago. For women, being part of a local team also significantly lowers the probability of coauthoring with a woman. The interaction effect between *publications in Top 5* and *female* is always negative and also significant in two out of six regressions (see cols. 4–9 in table 6). At first glance, this suggests that compared to senior male authors, senior women are more reluctant to coauthor with women. However, another, more plausible interpretation is that junior female economists have a wider choice of female coauthors than senior female economists. Computing the marginal effects in column 6 in table 6 at the average mean female share (12.6%), an increase in the mean female share of 10% raises the female probability of coauthoring with a woman by 17%, while it does not significantly affect male authors.

Table 7 presents the results of probit estimations of equation (11), where single authorship is the dependent variable. The entire sample of 3,090 articles is now used. In all specifications, women are more likely than men to single author. The probability of single authoring decreases as the *mean female share* increases. In specifications including an interaction effect between *female* and *mean female share*, female authors reduce their single authorship more as the *mean female share* increases. A consistent, although only weakly significant, pattern is that women affiliated with Harvard, MIT, or the University of Chicago tend to single author more than their male colleagues.

How do these results compare to the predictions of the model? The results of the estimations of equation (10), reported in table 6, show that the female propensity to coauthor with a woman increases more than the male propensity to coauthor with a woman as the share of female researchers increases, $\beta_3^{FTM} > 0$. In terms of the model presented in Section II, this implies that $\beta_f^{FTM} > \beta_m^{FTM}$. The hypothesis of gender irrelevance, which stated that authors were neutral regarding the gender of teammates and that men and women had the same preferences over team size, is clearly not consistent with the data since it does not allow for $\beta_f^{FTM} > \beta_m^{FTM}$ (see proposition 1). What about gender neutrality? It was illustrated in figure 1 that team formation can be gender neutral even if women have a higher propensity than men to coauthor with women. In this case, when $\beta_f^{FTM} > \beta_m^{FTM}$, gender neutrality requires that men single author more than women. All the specifications in table 7 indicate that women single author more, rather than less, compared to men. Hence, we are able to reject gender-neutral team formation. Even when controlling for differences across authors, fields, team, and articles, gender does matter for team formation in economics. The common idea that economists do not coauthor with women to any significant extent because there are no women to coauthor with is thereby incorrect. Our results in fact suggest the opposite, namely, that, as the share of women increases, the gender gap in the propensity to coauthor with a woman increases as well. Thus, there are no indications that gender sorting in teams automatically disappears as more women enter the profession.

Our results are, however, based on a restrictive sample of journals. The sample has been chosen primarily to control for the quality of output of the teams formed. Arguably the coauthorship pattern found in these top journals reflects the preference rankings at least at the top of the ability distribution. Have we detected gender preferences or not? It is possible to argue that we have not, if we believe that the men and women at the top have very different publication strategies. But even if men and women were to have different cutoff quality levels for when they judge a paper good enough to send to these journals, the low rates of acceptance are likely to undo any such biases since the cutoff quality for publication is likely to exceed the cutoff quality for submission for all authors and all team types. Another concern is that what we see is the effect of a refereeing process that discriminates against some types of teams. But according to Blank (1991), there is no evidence of bias against any sex in the referee process of these journals.

C. Robustness of the Results

This section tests the robustness and stability of the main results by including additional controls and alternative measures and by varying the sample. First, we include one new control, *recurrent team*. *Recurrent team* is a binary variable that takes the value one if an article is written by a constellation of coauthors that appears more than once in our data. Column 1 in table 8 shows that this variable does not enter significantly.

We also test an alternative measure of author seniority. Instead of using the number of publications, we use the year of the author's *first publication in Top 5*.[30] As column 2 indicates, the probability of having a female coauthor increases, the more recent the first publication of the author is. There are, however, no gender-specific effects.

In columns 3 and 4 of table 8, we investigate the effects of altering the sample. In column 3 all the observations from *AER*'s May issues (*Papers and Proceedings* of the AEA meetings) are excluded, together with the conference volumes of *JPE*. The results remain qualitatively the same. If anything, the gender gap in the probability to coauthor with a woman increases slightly. Column 4 reports the results when we include all articles, that is, single-authored articles, articles with two authors, as well

[30] Controlling for both measures simultaneously yields insignificant parameter estimates due to multicollinearity.

Table 7
Probit Estimation Results with Single Authorship as the Dependent Variable

	Probability of Single Authoring (*S*)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Characteristic of the author:							
Female	110.915***	112.172***	107.669***	122.230***	104.339**	122.925***	105.291**
	(41.088)	(41.016)	(41.089)	(41.505)	(42.440)	(41.569)	(42.351)
Publications in Top 5			.006**	.005	.005	.005	.005
			(.003)	(.003)	(.003)	(.003)	(.003)
Female × publications in Top 5			−.029	−.037	−.035	−.037	−.035
			(.023)	(.025)	(.024)	(.025)	(.024)
Affiliation to Top 3				.102	.101	.101	.100
				(.066)	(.066)	(.066)	(.066)
Female × affiliation to Top 3				.389*	.384*	.390*	.384*
				(.220)	(.218)	(.220)	(.218)
Characteristic of the field(s):[a]							
Mean female share (T3T3)	−3.880**	−3.313*	−3.198*	−3.157*			
	(1.851)	(1.882)	(1.885)	(1.877)			
Female × mean female share (T3T3)		−2.953	−3.068*	−3.347*			
		(1.808)	(1.808)	(1.827)			

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean female share (T3EconLit)						−2.504 (1.764)	
Female × mean female share (T3EconLit)						−3.507* (1.859)	
Mean female share (AEAT3)					−.849 (1.364)		
Female × mean female share (AEAT3)					−2.282 (1.704)		
Mean female share (AEAEconLit)							−.823 (1.369)
Female × mean female share (AEAEconLit)							−2.292 (1.711)
Pseudo R^2	.0406	.0412	.0424	.0444	.0432	.0439	.0428

NOTE.—Robust standard errors are in parentheses; constant is not reported, but it is always positive and significant; $N = 3{,}090$.

[a] Data source for female share, *i*, and field size, *j*, is in parentheses (*ij*), where the sources for *i* and *j* are T3 = *AER*, *JPE*, and *QJE*, 1991–2002; EconLit = all articles in EconLit, 1991–2002; and AEA = American Economic Association membership directories, 1993, 1997, and 2002.

* Significant at the 90% level.

** Significant at the 95% level.

*** Significant at the 99% level.

Table 8
Robustness Checks with Female Teammate as the Dependent Variable

	Probability of Having a Female Teammate (*FTM*)			
	(1)	(2)	(3)	(4)
Characteristic of the first author:				
Female	6.636	13.804	69.586	−23.640
	(73.212)	(72.583)	(108.225)	(55.377)
Publications in Top 5	−.002		.014	−.014*
	(.010)		(.010)	(.008)
Female × publications in Top 5	−.064		−.132*	−.086**
	(.042)		(.079)	(.040)
First publication in Top 5		.014**		
		(.007)		
Female × first publication in Top 5		.005		
		(.024)		
Affiliation to Top 3	−.392**	−.411***	−.377*	−.189
	(.163)	(.154)	(.202)	(.116)
Female × affiliation to Top 3	.016	−.054	−.142	−.308
	(.372)	(.361)	(.513)	(.310)
Characteristic of the field(s):[a]				
Mean female share (T3T3)	−1.310	−1.393	1.727	−.042
	(3.855)	(3.919)	(4.931)	(2.873)
Female × mean female share (T3T3)	10.766***	10.743***	14.310***	7.552***
	(3.165)	(3.120)	(4.553)	(2.401)
Characteristic of the team:				
Local team	.108	.115	.087	.405***
	(.115)	(.116)	(.142)	(.094)
Female × local team	−.813***	−.826***	−1.481***	−.384*
	(.271)	(.267)	(.573)	(.230)
Senior	.471***	.596***	.305**	.870***
	(.118)	(.119)	(.132)	(.090)
Female × senior	.169	−.031	.898*	.325
	(.301)	(.313)	(.465)	(.260)
Recurrent team	−.099			
	(.127)			
Observations	1,346	1,346	968	3,090
Pseudo R^2	.1194	.1215	.0889	.1543

NOTE.—Robust standard errors are in parentheses. In cols. 1–3, only articles with exactly two authors are included; in col. 3 the articles from all *AER* May issues as well as the *JPE*'s conference volumes are excluded; and in col. 4 all observations are included.
[a] Data source for female share, *i*, and field size, *j*, is in parentheses (*ij*), where the source for *i* and *j* is T3 = *AER*, *JPE*, and *QJE*, 1991–2002.
* Significant at the 90% level.
** Significant at the 95% level.
*** Significant at the 99% level.

as articles with more than two authors. A dummy for more than two authors is also included but not reported. Again, the main results are not altered.[31]

[31] We have tried other alternative variables, three of which are particularly worth mentioning. First, as yet another measure of the mean female share, we have constructed an article-specific mean female share. This is calculated by excluding the article in question when computing the mean female share for the articles in

As a test of the stability of our results across the distribution of the mean female share, we include the square and the cube of the *mean female share* to capture potential nonlinearities. While none of the coefficients on the level, square, and cube of the *mean female share* are individually significant, they are jointly significant, indicating that we lack statistical power to distinguish them. As an alternative, we estimate whether the interaction of *female* with the *mean female share* is the same at the top and bottom thirds of the mean female share distribution. We find that the estimated coefficient is somewhat less positive at the top third of the distribution, while the coefficient for the bottom third does not differ significantly from the average effect when the sample consists of articles with two authors. However, when including single- and multiauthored articles, neither the top coefficient nor the bottom coefficient are significant, although they are jointly significant. Summing up, since we do not find any consistent differences in the magnitude or significance of the coefficients over the mean female distribution, we conclude that there is no evidence of nonlinearities in the mean female share. Thus, we do not find support for the hypothesis that women with strong gender preferences select into fields with more women nor for the hypothesis that gender preferences weaken as a result of learning when fields grow more integrated. The results are not reported.

As a last robustness test, we reshape our data set and use all 5,308 authors instead of the 3,090 articles as our observations. Excluding single-authored articles, the reshaped data set has 3,955 observations.[32] When author, rather than article, is the level of observation, the results, of course, do not depend on the randomizing device for the first author. Furthermore, it enables us to control for the author-specific characteristics of all authors, not only of the first author. The drawback is that each article appears as many times as there are authors, and hence the observations are not independent. To handle this, we cluster the residuals by article when we estimate equation (10). The results are presented in table 9. Columns 1–4 in table 9 differ with respect to which data sources have been used for the measure of *mean female share*. Table 9 reveals that the

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our sample. The results using this article-specific mean female share are both qualitatively and quantitatively close to identical to the *mean female share (T3T3)* used. Second, we have tested whether other measures of affiliation, such as an affiliation to one of the top 20 U.S. universities or being a National Bureau of Economic Research member, significantly affect the propensity of having a female coauthor. They do not.

[32] Estimating the probability of single authorship is inappropriate in this data set, since single-authored articles only show up once, while coauthored articles appear at least twice. This problem is not adequately solved by clustering the observations by articles.

Table 9
Estimation Results with Authors as the Level of Observation

	Probability of Having a Female Teammate (*FTM*)			
	(1)	(2)	(3)	(4)
Characteristic of the first author:				
Female	.103	49.976	−1.778	49.965
	(59.687)	(61.797)	(59.747)	(61.690)
Publications in Top 5	−.009	−.009	−.009	−.009
	(.006)	(.006)	(.006)	(.006)
Female × *publications in Top 5*	−.080**	−.084**	−.083**	−.086**
	(.041)	(.040)	(.041)	(.041)
Affiliation to Top 3	−.108	−.113	−.107	−.113
	(.091)	(.091)	(.091)	(.091)
Female × *affiliation to Top 3*	−.432	−.473	−.412	−.459
	(.361)	(.342)	(.362)	(.342)
Characteristic of the field(s):[a]				
Mean female share (T3T3)	4.199*			
	(2.309)			
Female × *mean female share (T3T3)*	7.445***			
	(2.571)			
Mean female share (T3EconLit)			3.950*	
			(2.135)	
Female × *mean female share (T3EconLit)*			7.839***	
			(2.639)	
Mean female share (AEAT3)		2.667		
		(1.687)		
Female × *mean female share (AEAT3)*		4.664**		
		(2.277)		
Mean female share (AEAEconLit)				3.080*
				(1.677)
Female × *mean female share (AEAEconLit)*				4.884**
				(2.285)
Characteristic of the team:				
Local team	.148**	.144**	.150**	.145**
	(.066)	(.066)	(.066)	(.066)
Female × *local team*	−.461**	−.468**	−.449**	−.460**
	(.194)	(.193)	(.194)	(.193)
Senior	.341***	.343***	.340***	.343***
	(.064)	(.064)	(.064)	(.064)
Female × *senior*	.371*	.418**	.374*	.421**
	(.198)	(.194)	(.198)	(.195)
Pseudo R^2	.0984	.0957	.0988	.0965

Note.—Robust standard errors are in parentheses; constant is not reported, but it is always positive and significant; $N = 3{,}955$.

[a] Data source for female share, *i*, and field size, *j*, is in parentheses (*ij*), where the sources for *i* and *j* are T3 = *AER*, *JPE*, and *QJE*, 1991–2002; EconLit = all articles in EconLit, 1991–2002; and AEA = American Economic Association membership directories, 1993, 1997, and 2002.

* Significant at the 90% level.

** Significant at the 95% level.

*** Significant at the 99% level.

estimation of equation (10), with authors as observations, yields qualitatively very similar results to those reported in table 6.

V. Concluding Remarks

We have modeled the formation of teams as a random matching process influenced by the team members' preferences for team size and gender of teammates. We have then tested a set of hypotheses on the distributions of gender and team preferences on the pattern of authorships in articles published during 1991–2002 in three top economics journals. We find that the female-male gap in the propensity to coauthor with a woman increases with the presence of women in the field of research. This, together with the finding that women single author significantly more than men, allows us to reject the assertion that team formation in economics is gender neutral. Various robustness checks confirm that the pattern in the data is incompatible with gender neutrality. We can therefore conclude that there is indeed evidence of gender sorting in team formation. Our results show, counter to the common notion, that the relative lack of gender-mixed teams in economics will not automatically disappear as the pool of potential women coauthors increases.

The main contribution of our article is that we have established that there is gender sorting in team formation also at the field level in economics. Although there is evidence that male and female researchers choose different fields of specialization, we can conclude that the observed gender pattern in team formation is not due to gender sorting into fields or to differences in returns to coauthorship across fields, nor does it seem to be driven by gender differences in affiliations or seniority. It remains the task of future research to uncover the driving forces of gender sorting in team formation and determine to what extent they are taste based or productivity based.

At a more general level, gender sorting in team formation driven by some form of gendered preferences may be part of the explanation for why we observe persistent gender segregation on the labor market. Our findings suggest that gender segregation may be linked to the prevalence of teamwork. However, while academia, and economics in particular, is excellent for studying team formation since team formation is voluntary and productivity easily measured, there are at most 22% women in any of the major subfields of economics. Hence, a study of economics does not reveal what would happen to gender sorting if the fraction of women increased beyond this level. It is possible that there are learning effects and that gender sorting becomes less important with more balanced gender ratios, but there is nothing in the data pointing in that direction so far.

Appendix A

Proofs of Propositions 1 and 2

Proposition 1 Proof. If $\sigma_f = \sigma_m = \sigma$, $\mu_f = \mu_m = \mu$, $\kappa_m = \kappa_f = \kappa$, and $\nu_f = \nu_m = 1$, then $P(FTM \mid i) = (1-\sigma)^2\phi$ and $P(S \mid i) = 1 - (1-\sigma)^2$ for $i = m, f$.

Proposition 2 Proof. If $\nu_f = \nu_m = 1$,

$$P(FTM \mid m) = (1-\sigma_f)(1-\sigma_m)\phi,$$

$$P(FTM \mid f) = (1-\sigma_f)^2\phi,$$

$$P(S \mid m) = 1-(1-\sigma_m)^2 + (1-\sigma_m)(\sigma_f - \sigma_m)\phi, \text{ and}$$

$$P(S \mid f) = 1-(1-\sigma_f)(1-\sigma_m) + (1-\sigma_f)(\sigma_f - \sigma_m)\phi.$$

Hence, if $\sigma_m \gtreqless \sigma_f$, it follows that $\beta_m^{FTM} \lesseqgtr \beta_f^{FTM}$, $\alpha_m \gtreqless \alpha_f$, and $\beta_m^S \lesseqgtr \beta_f^S$.

Appendix B

Summary Statistics for Articles Published in *AER*, *JPE*, and *QJE* between 1991 and 2002

Table B1
Summary Statistics

Variable	Mean	SD	Min	Max
Characteristic of the team:				
Number of authors	1.72	.76	1	8
Female share of authors	.12	.29	0	1
Mixed team	.11	.31	0	1
Single authored	.44	.50	0	1
Local team	.19	.39	0	1
Characteristic of the first author:				
Female	.13	.34	0	1
Publications in Top 5	5.19	8.02	0	65
First publication in Top 5	1987.11	10.77	1950	2002
Characteristic of the article:				
Print year	1996.25	3.46	1991	2002
Number of pages	15.91	12.23	1	96
JPE	.19	.40	0	1
QJE	.17	.37	0	1
D–Microeconomics	.27	.44	0	1
E–Macroeconomics and Monetary Economics	.16	.36	0	1
F–International Economics	.10	.31	0	1
G–Financial Economics	.10	.30	0	1
H–Public Economics	.09	.29	0	1
I–Health, Education, and Welfare	.08	.27	0	1
J–Labor and Demographic Economics	.22	.41	0	1
L–Industrial Organization	.12	.32	0	1
O–Economic Development, Technological Change, and Growth	.14	.35	0	1
ZZ–Other	.11	.31	0	1

Table B1 (*Continued*)

Variable	Mean	SD	Min	Max
Characteristic of the field(s) of the article:*				
Mean female share (T3T3)	.13	.04	.08	.21
Mean female share (T3EconLit)	.13	.04	.08	.21
Mean female share (AEAT3)	.14	.04	.08	.26
Mean female share (AEAEconLit)	.14	.04	.08	.26
Mean single share (T3T3)	.42	.06	.27	.54
Mean single share (T3EconLit)	.42	.06	.27	.54
Mean single share in print year (T3T3)	.43	.12	.10	.82
Mean single share in print year (T3EconLit)	.43	.12	.10	.82

Note.—$N = 3{,}090$.
* Data source for female/single share, *i*, and field size, *j*, is in parentheses (*ij*). Sources are T3 = *AER*, *JPE*, and *QJE*, 1991–2002; EconLit = all articles in EconLit, 1991–2002; and AEA = American Economic Association membership directories, 1993, 1997, and 2002.

Appendix C

EconLit Classification

The JEL codes used in the analysis are those provided by EconLit. These are not necessarily the same as those given by the authors. The reason for using the EconLit JEL codes is that the articles published in the *JPE* do not have JEL codes. A further argument is that EconLit employs independent classifiers to assign JEL codes and key words to all articles. This makes the EconLit JEL codes more likely to be more consistent than JEL codes assigned by the authors themselves.

> We have no manual on classifications. Our classifiers (graduate and doctoral students of Economics), memorize the classification as they begin to use it. Their classifications are checked, and their misclassifications are discussed with them. The person in charge of classification (a University Professor of Economics) uses this method to maintain a high degree of consistency (although it can never be perfect). Economics is such a conceptual subject that differences in opinion are common. We try to classify articles under the subject descriptors (up to seven) where we think an economist would look to find such an article. We try to classify articles under the subject matter, not the theory (such as macroeconomics subdivisions). We put articles under the C, D, and E categories when the subject is the theory. (Personal communication with an employee at EconLit)

Table C1
JEL Classification Codes

Code	Description
A	General Economics and Teaching
B	Schools of Economic Thought and Methodology
C	Mathematical and Quantitative Methods
D	Microeconomics
E	Macroeconomics and Monetary Economics
F	International Economics

Table C1 (*Continued*)

Code	Description
G	Financial Economics
H	Public Economics
I	Health, Education, and Welfare
J	Labor and Demographic Economics
K	Law and Economics
L	Industrial Organization
M	Business Administration and Business Economics; Marketing; Accounting
N	Economic History
O	Economic Development, Technological Change, and Growth
P	Economic Systems
Q	Agricultural and Natural Resource Economics; Environmental and Ecological Economics
R	Urban, Rural, and Regional Economics
Y	Miscellaneous Categories
Z	Other Special Topics

Appendix D

American Economic Association Membership Directories

In order to obtain an independent source for the share of female researchers in the different subfields of economics, we have used the American Economic Association (AEA) membership directory. The AEA membership directory is only available for 3 years between 1991 and 2002, namely, 1993, 1997, and 2002. The directories contain self-reported information on main fields of interest, educational background, current position, and optional information on gender and race. These data are collected upon registration.

In the 1993 and 1997 directories, gender is missing for 25%–30% of the members. The 2002 membership directory unfortunately does not contain any gender information, as this was removed by the firm administering the directory. We have gender coded the missing information by using the U.S. Census Bureau's list of the most common names. From these lists, containing 1,219 male and 4,275 female names, we have computed the probability that the holder of any particular name is male or female.[33] We have matched this list to the AEA membership directory and thereby considerably improved our fraction of gender-coded AEA members not only for the year 2002 but also for 1993 and 1997 (see table D1). For the year 2002, which is the most problematic year in terms of

[33] After the 1990 U.S. Census, an independent postcensus operation (the 1990 Post-enumeration Survey [PES]) collected information about names and sex. The PES provides lists of male and female names and frequencies, covering 90% of the population. More information about frequent first names and methodology is available at http://www.census.gov/genealogy/names/.

missing gender information, this procedure facilitated moving from having gender information for old members only (constituting 51% of the 2002 members) to successfully gender coding 88% of the members. Table D1 reveals that women are somewhat more reluctant than men to state their gender in the AEA membership directory.

Table D1
Gender-Coding AEA Directories

AEA Directory and Coding Method	Gender-Coded Members				Total No. of Members
	Female	Male	Total Coded	As % of All Members	
1993 member coding	1,411	10,166	11,577	71	16,383
Row %	12	88	100		
1993 member coding + U.S. Census	2,204	12,824	15,028	92	
Row %	15	85	100		
1997 member coding	2,263	14,424	16,687	75	22,376
Row %	14	86	100		
1997 member coding + U.S. Census	3,249	17,728	20,977	94	
Row %	15	85	100		
2002 member coding	1,301	9,777	11,078	51	21,928
Row %	12	88	100		
2002 member coding + U.S. Census	3,230	16,062	19,292	88	
Row %	17	83	100		

Appendix E

Definition of Variables

Table E1
Variable Definitions and Sources

Variable	Definition	Source
Characteristic of the first author:		
Publications in Top 5	Author's number of publications in *AER*, *Econometrica*, *JPE*, *QJE*, and *Review of Economic Studies* from 1950 until the year of publication of the article in our sample	JSTOR
First publication in Top 5	Year of the author's first publication in *AER*, *Econometrica*, *JPE*, *QJE*, or *Review of Economic Studies* from 1950 onward	JSTOR
Affiliation to Top 3	Dummy if first author is affiliated to Harvard, MIT, or the University of Chicago	Own coding of affiliations in the *AER*, *JPE*, and *QJE* (T3) sample
Characteristic of the field(s) of the article:		
Mean female share (T3T3)	Weighted average of the female share in the JEL fields of the article, where the weights are the relative sizes of the JEL fields in each year; the female share by JEL field is computed as the share of female-to-male authors of all the articles in a JEL field weighted by the number of authors of each article	Based on *AER*, *JPE*, and *QJE* (T3) for both the female share and the annual size of the JEL fields
Mean female share (T3EconLit)	As above	Female share based on *AER*, *JPE*, and *QJE* (T3); annual size of JEL fields, all articles in EconLit
Mean female share (AEAT3)	As above, but annual female shares by fields are used; these are obtained by linear extrapolation from the point estimates obtained from the 1993, 1997, and 2002 registers	Yearly female share based on AEA membership directories; annual size of JEL fields, *AER*, *JPE*, and *QJE* (T3)

Mean female share (AEAEconLit)	As above	Yearly female share based on AEA membership directories; annual size of JEL fields, all articles in EconLit
Mean single share (T3T3)	Weighted average of the annual share of single authorship of the JEL fields of the article, where the weights are the relative sizes of the JEL fields in each year	*AER*, *JPE*, and *QJE* (T3) for both single share and annual size of JEL fields
Mean single share (T3EconLit)	As above	Yearly single share based on *AER*, *JPE*, and *QJE* (T3); annual size of JEL fields, all articles in EconLit
Team characteristic:		
Local team	Dummy that equals one if one coauthor has the same affiliation as the first author	*AER*, *JPE*, and *QJE* (T3)
Senior	Dummy that equals one if the first author has more publications than her coauthors	Based on JSTOR
Recurrent team	Dummy that equals one if the same constellation of authors appears at least twice in T3	*AER*, *JPE*, and *QJE* (T3)
Characteristic of the article:		
Print year	Year the article is published	*AER*, *JPE*, and *QJE* (T3)
Number of pages	Number of pages of the article	*AER*, *JPE*, and *QJE* (T3)
Source	Dummy for the journal in which the article is published	*AER*, *JPE*, and *QJE* (T3)

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