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Returns to Teamwork and Professional Networks: Evidence from Economic Research

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Abstract

Teamwork is growing in developed economies, and workers in teams are increasingly compensated according to team output. Because parsing individual contributions to teamwork is difficult, I focus on scholarly economics research, which lists contributing authors. I use turnover to identify *team value-added*: an author's average output quality conditional on the value-added of coauthors. Linking the universe of scholarly economic research output to publicly available payroll records, I study the effect of value-added on salaries. Strikingly, coauthors' value-added has a greater effect on salaries than does own value-added, suggesting the value of professional networks dominates the effect of discounting contributions based on coauthor quality. Moreover, authors are compensated for the solo-authored output of their coauthors – which can not be reasonably attributed to them – demonstrating the value of professional networks.

JEL codes: J16, J24, J33, J44.

Keywords: human capital, teamwork, productivity, performance pay, non-partite networks.

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1 Introduction

Teamwork is prevalent in developed economies, and growing. By the mid 1990s over 60% of US firms organized at least one-fifth of their workers in teams, and more recent data from the UK puts this figure at over 80%. By the turn of the millennium, a majority of workers in both countries worked predominantly in teams. Teamwork is especially prevalent in complex production processes,[1] including academic economic research, where coauthored work has replaced solo-authored as the dominant paradigm.

In the broader economy, compensation is increasingly dependent on team output. Among UK workers who report working 'usually' in teams, around 15% receive pay dependent on team output – up from 6% in the 1990s. This paper studies how academic economists are compensated for their perceived contributions to teamwork.

To investigate salary returns to coauthored papers, I build a value-added model that parses individual contributions based on the publication history of all coauthors. Intuitively: for a given quality of paper, the *reference author* is given less credit when the *coauthor* has a better publication history.[2]

Matching estimated value-added to publicly-available payroll data, I find the following:

1. One standard deviation increase in own solo-authored productivity predicts $10,000 higher salary (2015 USD).
2. One standard deviation increase in own team value-added predicts $15,000 higher salary.
3. One standard deviation increase in coauthors' team value-added predicts $20,000 higher salary.
4. One standard deviation increase in coauthors' solo productivity predicts $9,500 higher salary.

These findings are robust to a variety of specifications and output definitions.

These results speak to the way academic departments form beliefs over the contributions of their employees to teamwork. Crucially, I reject the 'rule-of-thumb' that estimates a given author's contribution to a coauthored work by dividing paper quality

[1] Ichniowski and Shaw (2009), VersionOne (2020)

[2] The value-added model is mutually consistent, so the labeling of reference author and coauthor is arbitrary – everyone is the reference author from their own point of view.

by the number of authors. Effectively, the value-added model splits the total output of a coauthored paper into two portions: the portion attributed to the reference author, and the portion attributed to the coauthors. If departments used the rule-of-thumb when determining salaries, these two portions should have equal effect on salaries. Surprisingly, I find that a unit increase in coauthor value-added predicts higher salary than a unit increase in own value-added. This finding is consistent across specifications and is highly significant for women (p-values 0.0081–.021), moderately significant for men (p-values 0.056–0.071) and marginally significant for the pooled sample (p-values 0.094–0.21). This counterintuitive result is consistent with an environment where departments value professional networks in the form of coauthorship relationships with higher-achieving coauthors.

I also find direct evidence of value of professional networks in academia. Reference authors receive significantly higher compensation based on their coauthors' *solo-authored* output, which cannot be reasonably attributed to the reference author. This is consistent with the notion of Montgomery (1991) that homophily in social networks implies that a connection to a higher productivity individual in turn signals one's own productivity. Departments observing their employees working with better coauthors may revise up their beliefs about their employee's unobserved quality. Hensvik and Skans (2016) find evidence consistent with this in the broader labour market. Likewise, a connection to a higher-quality coauthor may give an employee credible outside options that can be used to negotiate a higher salary.

I contribute to related literatures studying how best to measure academic output, and how to relate it to compensation. The problem of attributing individual contributions to coauthored work is well known. Consider a 'reference author' i whose salary we observe, who has produced a paper along with N total coauthors (including the reference author). Hilmer et al. (2015) outlines three approaches to estimating i's contribution: (i) ignore coauthors and attribute completely to i; (ii) divide by N; (iii) divide by N^c, where $c \in \{0, 1\}$ (see Ellison 2013).[3] I collectively refer to these as the rules-of-thumb. Sen et al. (2014) and Hilmer et al. (2015) find that rule-of-thumb productivity estimates predict higher salaries in academic economics.[4]

[3] In principle any of these three approaches – as well as the novel method I introduce in this paper – can be applied to quantity or quality of output, or both. Ellison (2013) applies approach (iii) to Hirsch (2005)'s H-index, which incorporates both quantity and quality.

[4] Hamermesh and Pfann (2012) and Ellison (2013) use department rank as the outcome in the absence of salary data.

Each rule-of-thumb implies that credit for a coauthored paper is assigned equally to each coauthor. However, this is unlikely to be the case.[5] The current paper is part of a new strand of literature that relaxes this assumption, instead calculating $value - added$ that varies according to the publication history of each author. Ahmadpoor and Jones (2019) estimates value-added for scientists, along with the elasticity of substitution between inputs. Bonhomme (2020) considers an additive model of value-added, as well as an alternative that allows for complementarity, and makes applications to economics research papers as well as patent data. Value-added estimation is standard in the literature on teacher performance evaluation (see Chetty et al. 2014 and many others) and is being introduced into other settings.[6]

My method is most closely related to the additive model of Bonhomme (2020). However, I relax one important assumption compared to the previous papers: I allow value-added to coauthored work to vary with respect to solo productivity. That is, I estimate two productivity measures for each researcher: one for solo-authored papers and one for coauthored papers. This is a first-order concern both because teamwork may involve different skills compared to solo work (Deming 2017, Devereux 2018), and because attribution of credit for teamwork involves ambiguity that attribution for solo work does not, particularly in academic economics (Sarsons et al. 2020). I find that solo productivity and team value-added vary within researcher: their correlation is around 0.4.

My results also complement a recent literature showing coauthorship patterns matter for academic output (Ductor et al. 2018) and tenure decisions (Sarsons et al. 2020). These papers find that men and women exhibit different coauthorship patterns, and that departments form different beliefs over their employee's contributions depend on the gender of the employee and that of the coauthors. I test whether own and coauthor gender matter for salary levels, but find only minor differences.

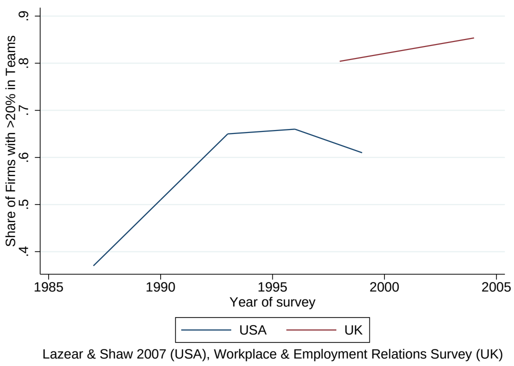
The remainder of the paper is organized as follows. Section 2 explains the bibliographical research data, the payroll data, and the matching process that links the two. Section 3 presents the empirical modeling framework, including a discussion of network exogeneity, and section 4 covers the identification and estimation of this model. Section 5 presents the main results, as well as results broken up by gender. For robustness of the results see appendix A.

[5] Consider a star researcher j who produces many top publications, and one day decides to work with a mediocre researcher i. If the research output produced by team ij is top quality work, observers likely attribute more credit to j than to i.

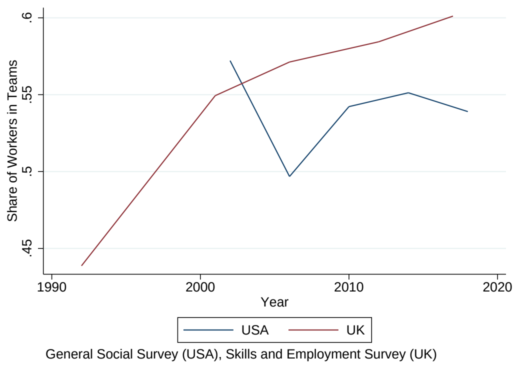
[6] See Helal and Coelli 2016, Isphording and Zölitz 2020, Stoye 2020.

Figure 1: Teamwork and Team Compensation

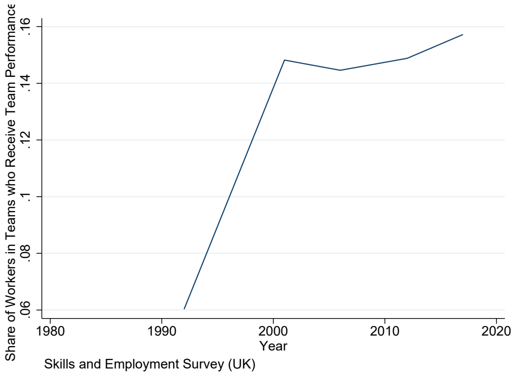
(a) Firm Surveys



(b) Worker Surveys



(c) Team Performance Pay



(d) Teamwork in Economics

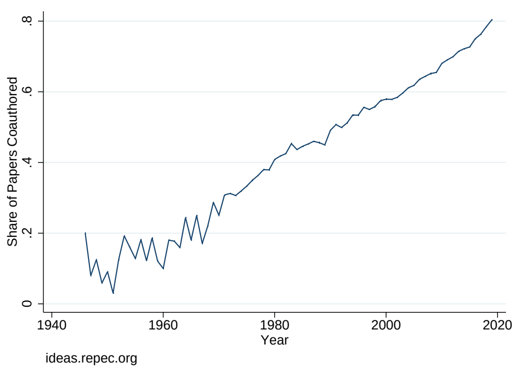


Table 1: Summary Statistics, RePEc Articles

	Mean	Median	Stdev	Min	Max	N
Year	2004.64	2008	12.01	1900	2019	524039
Number Authors	1.86	2	.76	1	3	524039
Citations	11.94	2	58.33	0	8303	524039
Journal Impact Factor	1.2	.46	2.06	0	15.28	524039

This table reports summary statistics for the estimation sample of articles listed in the RePEc database. The unit of observation is an article. I limit the sample to papers written by authors in the largest connected component of the coauthorship network, for whom value-added can be identified (see section 4 for details).

Table 2: Summary Statistics, Payroll Records

	Mean	Median	Stdev	Min	Max	N
Year	2015.09	2015	2.69	2011	2019	4501
Earnings	249489.7	226214.9	103879.3	100539.2	666291.1	4501
Years Experience	10.39	8	9.17	1	61	4501
Male	.85	1	.35	0	1	4501
Number Pubs.	15.47	11	15.46	1	122	4501
Number Solo Pubs.	3.69	1	6.71	0	66	4501
Number Co. Pubs.	3.04	2	2.11	1	17	4501

This table reports summary statistics for employees of economics and business departments in the University of California system whose first name/middle initial and last name match to authors from the sample of RePEc bibliographical records given in table 1. The unit of observation is an employee-year. Years of experience is given as the difference between the year of the payroll record and either the first year the employee appears in the records, or the earliest year that author has published – whichever is earlier. I impute gender based on first name frequencies given by the US social security database.

2 Data

I combine bibliographical records of research output with publicly available payroll records to create a novel dataset that contains both productivity and earnings for a large sample of professional academics. In this section I describe the research database, the payroll records, and the matching process. I also infer author gender based on US social security records.

2.1 Researcher Data

The Research Papers in Economics (RePEc) database catalogues the near-universe of scholarly publications in economics and sister fields, listing over 2000 journals, each with a comprehensive list of the articles published within. As of the date of access in autumn 2019, this included over 1.9 million articles, with the earliest being an archival document dating back to 1710. Each article within a journal contains three key variables: the names of authors, the citation count, and the year of publication. An article is also of course associated with the journal of publication. More recent articles in more recognized journals also contain additional information such as the abstract, keywords, and JEL codes, which I do not make use of at present.

The unit of observation is an article, whose quality I measure alternatively by its citation count or by the impact factor of the journal in which it is published. Each article is attributed to $n \geq 1$ authors. I match authors by name across articles to create a panel dataset of researcher publications in a coauthorship network. The structure of the resulting dataset is comparable to that of matched firm-worker panel datasets.

2.2 Sample Selection

I begin by dropping any article for which the year of publication is not recorded. I discard articles in unranked journals (which have an impact factor of zero) and articles whose authorship is unreported or attributed to an institution or editorial board. I limit the sample to articles attributed to three authors or fewer, preserving over 80% of all articles. For multiple-authored papers I limit the sample to the largest connected component of the coauthorship network.[7] I also drop 'inseparable' authors – pairs of authors who coauthor every paper together – because I cannot distinguish between their

[7] This facilitates value-added analysis, since each author within a connected component can be indirectly compared to any other in that component. See section 4 for a discussion.

contributions. Table 1 reports summary statistics for the selected sample.

2.3 Payroll Data

Payroll data come from public sector disclosures provided by the Nevada Policy Research Institute (NPRI). The NPRI requests payroll records from government organs in California and Nevada and disseminates non-anonymized data through transparentcalifornia.com and transparentnevada.com.[8]

Because records originate from different state and sub-state level jurisdictions, they are not reported in a consistent format. I restrict the sample to the University of California system because it provides the department of employment in the job title, which limits the scope for false-positive name matches. I look for first name/middle initial and last name matches to the researcher data. Matching to authors from the largest connected component of the RePEc database yields an unbalanced panel of payroll records for over 1300 employees spanning from 2011 to 2019, the range of years for which earnings are reported. So as to exclude temporary and visiting appointments, I limit the sample to individuals earning $100,000 USD and over per year.

2.4 Gender of First Names

Every year, the US Social Security Administration reports frequencies of births, by gender, for each given name that has at least five occurrences. I impute gender of employees based on the share of individuals of either gender with the given first name. Nearly 90% of employees have a first name that is associated with one gender or the other in over 90% of cases.

I estimate solo productivity and team value-added agnostic of gender, making use of imputed gender only when analyzing earnings.

3 Empirical Model

This section introduces the value-added production functions that I use to analyze researcher productivity, and the Mincerian earnings function that I use to link productivity to earnings.

[8] Card et al. (2012) and Mas (2017) study the impact of public disclosure in the university and public sector contexts respectively.

3.1 Production

I extend the framework of Devereux (2018) to allow for teams of size $n > 2$. This is similar to the additive model of Bonhomme (2020), except that I allow solitary productivity to vary disjointly from team value-added.

Consider a set of N workers, each characterized by a double $\{\alpha_i, \beta_i\} \in \mathbb{R}^2$ which gives solo productivity and team value-added respectively. I impose no restriction on the relationship between a worker's solo productivity with respect to the team value-added; a worker may be unproductive on one's own but highly productive in a team ($\alpha_i << \beta_i$), or vice versa ($\alpha_i >> \beta_i$).

Solo productivity is given by:

$$y_{ip} = \alpha_i + \varepsilon_{ip} \tag{1}$$

where i indexes an individual and p the specific project. Output y_{ip} gives the productivity of a particular project, with α_i giving the average productivity of worker i.

Workers can also form production teams of size $n \in \{2, 3\}$. A team τ is a set of workers $\{i, j\}$ or $\{i, j, k\}$. The output of a team τ on a project p is given by:

$$y_{\tau p} = \lambda_n + \sum_{i \in \tau} \beta_i + \varepsilon_{\tau p} \tag{2}$$

where β_i gives an individual i's value-added to team production, and λ_n is a scaling parameter for a team of size n. Without loss of generality, normalize $\lambda_2 = 0$. Equation (2) sums the value-added inputs of workers $i \in \tau$, allowing for either economies of scale ($\lambda_3 > 0$) or coordination costs ($\lambda_3 < 0$), or for team size to be neutral ($\lambda_3 = 0$). Identical teams may work on multiple projects.

The estimates α and β give solo productivity and value-added for each worker in units of output. Solo productivity α is the simple average of output produced by a solitary worker. and team value-added the conditional average of the output that worker produces in teams (conditional on teammate inputs). With additional assumptions these can be interpreted as latent skill factors (Devereux 2018, Bonhomme 2020). Namely, assuming that teammate matching is random conditional on unobservables ensures unbiasedness of skill estimates. In this case, experimentally assigning workers i and j to work on a project should produce $\hat{\beta}_i + \hat{\beta}_j$ in expectation. However, if workers seek out partners with whom they are idiosyncratically well matched to – teams that 'click' – then matching a worker i to a random teammate j produces output smaller that $\hat{\beta}_i + \hat{\beta}_j$ in expectation. In this case the $\hat{\beta}$ parameters pick up some share of the idiosyncratic match quality on the basis of which workers select teams; $\hat{\beta}$ then should not be interpreted as an estimate of latent skills. However, $\hat{\beta}$ is an unbiased estimate of realized research achievement regardless of whether authors sort based on match effects.[9]

3.2 Earnings

I explain earnings using a Mincerian earnings regression that incorporates individual productivity and the productivity of partners. A worker i's earnings are given as follows:

$$W_{it} = \mu + \hat{\alpha}_i w_a + \hat{\beta}_i w_b + \bar{\alpha}_{J(i)} s_a + \bar{\beta}_{J(i)} s_b + X_{it} b + \varepsilon_{it} \tag{3}$$

where $\hat{\alpha}_i$ and $\hat{\beta}_i$ are the estimated productivity parameters given in the previous subsection, and X_i contains observable factors such as experience and job tenure. Then w_a gives the earnings returns to solitary productivity, w_b to team value-added, and b the returns to observables. Because productivity measures are static, I cluster all regressions at the author level.

The terms $\bar{\alpha}_{J(i)}$ and $\bar{\beta}_{J(i)}$ give the average productivity of partners in either domain. Letting $J(i)$ be the set of teammates i works with, the former is defined as $\bar{\alpha}_{J(i)} \equiv \frac{1}{n_i} \sum_{j \in J(i)} \alpha_j$, where n_i is the number of partners of i. $\bar{\beta}_{J(i)}$ is similarly defined. Then s_a gives the earnings returns to the average solo productivity of partners, and s_b gives the returns to partners' average team value-added.

Earnings returns to solo-authored work are straightforward because there is no ambiguity over who has contributed to the papers in question. I expect departments to pay higher salaries to authors who write better solo papers; that is, $\hat{w}_a$ should be positive and significant. Conversely, the quality of solo papers written by author i's coauthors cannot be directly attributed to i. However, the fact that higher solo-productivity coauthors have chosen to work with i may signal i's unobservable quality, and the value of having them as partners may be priced by departments.[10] In this case I expect the estimate $\hat{s}_a$ to be positive and significant. However, a unit increase in own-work quality must be valued higher than whatever spillovers arise from the same increase by one's coauthor, so I expect that $\hat{w}_a > \hat{s}_a$.

[9] Ong et al. (2018) shows that authors select into single versus coauthored work based on the initial letter of their surname. Such incentives could be used as a source of exogenous variation to identify latent skill parameters rather than realized research achievement.

[10] Professional connections may increase productivity, or provide outside options. I do not attempt to distinguish between these channels at present.

The returns to coauthored papers are more nuanced, because there may be uncertainty over who to attribute the success of coauthored papers to. By construction, coauthored paper quality is the sum of the value-added inputs for each author; for any given author, the average quality of their coauthored papers is $\hat{\beta}_i + \bar{\beta}_{J(i)}$. The value-added model attributes the portion $\hat{\beta}_i$ to author i, and $\bar{\beta}_{J(i)}$ to the partners, based on the entire coauthorship history of each author. All else equal, if i's partners $J(i)$ write high-quality papers with other coauthors besides i, the value-added model attributes a relatively higher portion of output to i's partners $J(i)$ and less to i; that is, $\bar{\beta}_{J(i)}$ increases and $\hat{\beta}_i$ decreases.

Several issues arise. Departments may not use the value-added model when forming beliefs over who contributed to a coauthored paper's success.[11] If departments infer contributions by rules of thumb, like dividing perceived paper quality by the number of authors, then they should reward authors in equal proportions for work that the value-added model attributes to that author ($\hat{\beta}_i$) and for work the value-added model attributes to coauthors ($\bar{\beta}_{J(i)}$). The same pattern will emerge if departments do not discount coauthored papers at all.[12] Conversely, if departments infer a smaller contribution from author i for a paper of a given quality the better is the publication record of coauthors, then I expect $\hat{w}_b > \hat{s}_b$.

The above interpretation is complicated by spillovers. Departments may discount the contribution of an author i who works with high coauthorship-productivity partners, but value the professional networks that those coauthors provide, or take them as a signal of i's unobserved quality. In this case the estimated parameter $\hat{s}_b$ should be positive and significant.

Altogether, I expect the following. First, departments value the research output of their faculty, whether solo or coauthored. Departments discount authors' contributions according to the identity of their teammates in a way approximated by the value-added model, but allow for uncertainty when parsing authors' contributions. I expect that some of the output the value-added model attributes to coauthors will win the reference author higher earnings. At the same time, departments value the professional networks

[11] This could be the case even if the value-added model is the data-generating process for paper output, but departments do not believe or acknowledge this fact. Alternatively, the value-added model may be incorrectly specified, but departments believe it to be true; all the matters for salary determination is the latter.

[12] Sarsons et al. (2020) finds evidence that coauthorship with men reduces women's chances of getting tenured, indicating that departments do discount based of characteristics of the coauthors. I return to the issue of gender in section 5.

that good coauthors provide (or respond to credible outside options that good coauthors provide); this applies equally to solo and coauthored work of these coauthors. This implies that $\hat{w}_a > \hat{w}_b > \hat{s}_b > \hat{s}_a$.

4 Identification and Estimation

This section covers identification of worker value-added in teams of two and three. Like past work on teammate, manager, and teacher value-added, it relies on turnover to make comparisons between different individuals.[13] It is also closely related to the two-way fixed effects decomposition pioneered by Abowd et al. (1999).[14]

Consider a set of N workers producing alone and in teams of size $n \in \{2, 3\}$. Stacking all instances of equation (1) yields the following matrix equation

$$Y_1 = A\alpha + \varepsilon_1 \tag{4}$$

where α is an $N \times 1$ array of worker solo productivity parameters, and A is a $P_1 \times N$ design matrix, with P_1 being the total number of solo papers. The rows of A each sum to one, and the columns of A sum to the total number of solo papers written by the author corresponding to that column. Matrix A has full rank, and the solution $\hat{\alpha} = (A'A)^-1A'Y_1$ is recovered by textbook fixed-effects estimation.

Similarly, stack all instances of equation (2) into the following matrix equation

$$\begin{bmatrix} Y_2 \\ Y_3 \end{bmatrix} = \begin{bmatrix} 0 & B_2 \\ \iota & B_3 \end{bmatrix} \begin{bmatrix} \lambda_3 \\ \beta \end{bmatrix} + \varepsilon_{2,3} \tag{5}$$

where β is an $N \times 1$ array of worker team productivity parameters, and B_2 and B_3 are, respectively, $P_2 \times N$ and $P_2 \times N$ design matrices indicating which workers belong to any given observation (paper). Each row of B_2 each sums to two, and each row of B_3 to three, corresponding to the number of workers per team. The submatrices 0 and ι are commutable arrays of zeros and ones respectively, and the scalar λ_3 is the scaling factor for teams of three.

The submatrices B_2 and B_3 are incidence matrices that fully describe the networks of two- and three-authored papers respectively. Each author corresponds to a node, and

[13]For teammates, see Arcidiacono et al. (2017) and Devereux (2018). For managers, see Lazear et al. (2015) and Benson et al. (2019). For teachers, see Chetty et al. (2014), among many others.

[14]This seminal paper and the subsequent literature decompose wages into worker and firm residuals in a way that is mathematically identical to the two-person team case in the current study. However, since wages are a transfer from one party to another, these residuals cannot be interpreted as value-added.

each paper to an edge in the respective networks $\mathcal{B}_2$ and $\mathcal{B}_3$. Abowd et al. (2002) show that connectedness of $\mathcal{B}_2$ is sufficient to guarantee that B_2 has full rank. Intuitively, each author must have worked with some coauthor who has worked with some coauthor, and so on, such that there exists a path between every one of the N authors. This allows indirect comparisons of each author; somebody who works outside of this connected component cannot be compared to those inside.

Bonhomme (2020) gives a formal condition for identification of worker fixed effects in samples with teams of arbitrary size, and develops an algorithm to select a sample for which each worker is identified. I implement a similar algorithm, described in subsection 4.1. This results in a connected sample of teams of two and three, whose incidence matrix has full rank. The existence of any common author between the two- and three-authored samples guarantees that the overall matrix of covariates has full rank.

4.1 Estimation

To construct a sample of two- and three-authored papers for which all worker fixed effects are identified, I implement the following algorithm.

1. Select the largest connected component of authors among the sample of two-authored papers.

2. Select all papers written only by authors in this connected set (including two- and three-authored papers).

3. Add all three-authored teams composed of two selected authors, and one non-selected, if any.

4. Add all two-authored teams composed of one selected author, and one non-selected, if any.

5. Repeat until convergence.

This results in a connected network of authors for whom every fixed effect is identified. Crucially, no inseparable pairs – two coauthors who always work with each other – are included. See Bonhomme (2020) for a more general algorithm allowing for teams of arbitrary size, including teams of one.

Due to the large parameter space, the estimates $\hat{\alpha}$ and $\hat{\beta}$ prohibitively computationally-intensive to solve by matrix inversion. Instead I estimate equations (1) and (2) using the preconditioned conjugate gradient algorithm, which produces the exact OLS solution (see Abowd et al. 2002 for a discussion).

Because some authors have as few as a single paper in either the solo or coauthored categories, measurement error may bias my results. To account for this I calculate empirical Bayes shrinkage estimates of both solo productivity and team value-added (see appendix A for details). Calculating the empirical Bayes shrinkage estimates $\tilde{\alpha}$ and $\tilde{\beta}$ requires the standard errors of each element of the OLS estimates $\hat{\alpha}$ and $\hat{\beta}$. Typically these would be recovered from the variance-covariance matrix. However, calculating the variance-covariance matrices requires inverting $A'A$ and $B'B$ respectively, which is prohibitively computationally-intensive. Moreover, the variance-covariance matrices are of dimensions $N \times N$ and $(N+1) \times (N+1)$ respectively, with each element falling along the real line. The large dimensions and high precision required make even storing in memory the variance-covariance matrix prohibitive. To retrieve standard errors, I employ the sparse inverse algorithm due to Takahashi (1973) to calculate the sparse variance-covariance matrix; this contains zeros except for the diagonal elements – the standard errors of parameter estimates – and elements corresponding to the covariance between parameter estimates for any authors who have coauthored together. This has a form resembling the Laplacian matrix of the coauthorship network.

Recovering both the exact OLS solutions of productivity estimates and the exact standard errors corresponding to each estimate, I proceed to analyze the relationship between estimated productivity and salaries in the following sections.

5 Results

Table 3 presents the main results. One standard deviation increase in solo productivity predicts around \$10,000 higher earnings in 2015 USD, while a standard deviation in team value-added predicts around \$15,000 higher earnings. One standard deviation increase in the average team value-added of partners predicts around \$20,000 higher earnings, and a standard deviation increase in the average solo productivity of coauthors predicts around \$9,500 in increased earnings.[15] Appendix A presents a variety of alternative specifications, demonstrating the robustness of these results.

The results reveal several important stylized facts about research productivity and pay. By construction, average own value-added ($\hat{\beta}$) and average coauthor value-added

[15]The difference in effects between partner and own value-added is only marginally significant in the pooled sample, but is highly significant when I consider genders separately (see table 4).

Table 3: Coauthor Spillovers onto Own Earnings

	b/se	b/se	b/se	b/se	b/se
Experience	2058.9***	2143.2***	2116.7***	1926.6***	2130.4***
	(236.5)	(240.1)	(238.8)	(270.4)	(284.8)
Own $\hat{\alpha}$	17052.2***		10702.1**	11357.0***	10556.1**
	(4146.2)		(4302.9)	(4351.2)	(4344.6)
Partner $\bar{\alpha}$	20034.5***		9583.4**	9515.3**	9464.3**
	(3663.3)		(4054.5)	(4036.1)	(4088.1)
Own $\hat{\beta}$		22949.7***	14433.0***	14531.9***	14757.5***
		(3108.3)	(3619.6)	(3663.5)	(3707.0)
Partner $\bar{\beta}$		29266.1***	19229.6***	19794.0***	19569.5***
		(3981.8)	(4727.7)	(4704.2)	(4751.7)
Has Solo Pub.				-9401.1	-4500.3
				(6783.2)	(6896.1)
# Total Pub.				594.3***	
				(215.3)	
# Solo Pub.					-52.2
					(534.1)
# Duo Pub.					1168.6
					(1567.9)
Constant	184769.8***	182179.7***	177609.2***	177395.7***	176865.4***
	(5732.6)	(5709.7)	(6069.6)	(6469.2)	(6860.3)
p($\hat{\beta} = \bar{\beta}$)		0.094	0.21	0.17	0.21
N	4501	4501	4501	4501	4501
R^2	0.11	0.11	0.12	0.13	0.12

This table presents the effect of solo productivity and team value-added on annual earnings (in 2015 USD). Solo productivity α and team value-added β are each measured in units of one standard deviation. These standard deviations are common to the distribution of own productivity estimates as well as those of partners. Partner productivity is given as the average of solo productivity or team value-added of all coauthors. All specifications cluster standard errors at the author level.
*** $p < .01$, ** $p < .05$, * $p < .1$

(partner $\hat{\beta}$) sum to the average output of coauthored papers. Intuitively, the value-added model splits the output value of coauthored papers – attributing some fraction to the reference author, and the remainder to the coauthors – based on the publication history of all authors. If departments do not discount an author's contribution to coauthored papers based on the publication history of the coauthors (or if they discount in proportion to the number of coauthors) then $\hat{\beta}$ and partner $\hat{\beta}$ should yield approximately equal coefficients in the earnings regression. The fact that own value-added (as attributed by the value-added model) predicts significantly lower earnings than the fraction of coauthored research output attributed to coauthors suggests that professional network effects outweigh discounted attribution of credit. The fact that coauthor value-added spills over onto own earnings may imply a degree of uncertainty over research contributions: authors may receive partial credit for the work done by their coauthors. Alternatively, departments observing their employees collaborating with more successful coauthors may revise up their beliefs about their own employee's unobserved ability, or collaborating with higher-productivity coauthors may provide authors with outside options that they use to negotiate higher salaries.

The spillover of coauthor solo productivity onto own earnings has a narrower interpretation. This productivity cannot reasonably be attributed to the reference author, whose name is not listed on those papers. Therefore I conclude that it must be due to the value of professional networks, either by providing a better outside option or by signaling higher unobserved productivity of the reference author by virtue of being matched to a higher-productivity coauthor. The difference in magnitude between the spillover generated by the $\hat{\alpha}$ and the $\hat{\beta}$ of coauthors speaks to the fact that the latter may be reasonably attributed (in part) to the reference author. This is the case either in a limited-information environment wherein the value-added model is the true data generating process of research output, or if the value-added model is misspecified.

5.1 Gender Heterogeneity

In this subsection I investigate heterogeneity in the main results depending on the gender of the reference author as well as that of the coauthors. Sarsons et al. (2020) finds that attribution of value-added to coauthored work depends on the gender of either party when it comes to tenure decisions. I revisit this question using salary as the outcome of interest.

Table 4 allows returns to productivity, as well as spillovers generates by coauthors,

Table 4: Coauthor Spillovers onto Own Earnings by Own Gender

	b/se	b/se	b/se	b/se	b/se
Experience	2020.8***	2099.9***	2066.4***	1933.7***	2109.5***
	(238.2)	(243.7)	(240.6)	(274.9)	(289.3)
Male	28017.1***	21970.9**	31087.3***	30088.7***	32071.4***
	(10478.4)	(10807.5)	(10466.5)	(10521.2)	(10488.3)
Own $\hat{\alpha}$	30090.4**		25638.5**	25847.5**	25508.0**
	(12146.1)		(12583.2)	(12629.6)	(12596.9)
Own $\hat{\alpha}$ × Male	-16084.3		-18417.4	-18098.7	-18506.5
	(12808.7)		(13269.2)	(13249.8)	(13215.4)
Partner $\bar{\alpha}$	22597.3**		11872.2	13724.7	13319.3
	(10015.5)		(10610.3)	(10554.7)	(10540.5)
Partner $\bar{\alpha}$ × Male	-3105.9		-3136.2	-3980.4	-3950.6
	(10735.3)		(11465.5)	(11517.0)	(11536.8)
Own $\hat{\beta}$		28946.8***	9895.3	10194.8	10049.5
		(7614.9)	(8682.6)	(8756.8)	(8811.3)
Own $\hat{\beta}$ × Male		-6695.1	5724.3	5299.9	5747.2
		(8309.4)	(9544.3)	(9536.3)	(9606.1)
Partner $\bar{\beta}$		49065.8***	28636.4**	29208.4**	28946.9**
		(8333.6)	(11733.4)	(11608.6)	(11641.6)
Partner $\bar{\beta}$ × Male		-23236.7**	-10749.3	-11027.8	-10931.0
		(9427.4)	(12806.6)	(12640.7)	(12691.5)
# Total Pub.				588.0***	
				(213.9)	
Has Solo Pub.				-9256.2	-4721.7
				(6681.4)	(6787.8)
Partner Has Solo Pub.				-3925.3	-2750.2
				(14076.2)	(13927.9)
Male Partner Has Solo Pub.				-3997.9	-3160.4
				(11802.8)	(11722.4)
# Solo Pub.					-25.0
					(539.5)
# Duo Pub.					1236.5
					(1592.9)
Constant	161827.4***	164110.2***	152128.1***	158016.1***	154510.5***
	(9755.2)	(9837.4)	(9556.9)	(11688.3)	(11906.1)
p($\hat{\beta} = \bar{\beta}$)		0.0081	0.021	0.017	0.019
p($\hat{\beta} = \bar{\beta}$), Males		0.056	0.071	0.068	0.066
N	4501	4501	4501	4501	4501
R^2	0.11	0.12	0.13	0.13	0.13

This table presents the effect of solo productivity and team value-added on annual earnings (in 2015 USD). Solo productivity α and team value-added β are each measured in units of one standard deviation. These standard deviations are common to the distribution of own productivity estimates as well as those of partners. Partner productivity is given as the average of solo productivity or team value-added of all coauthors. All specifications cluster standard errors at the author level.

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

Table 5: Coauthor Spillovers onto Own Earnings by Coauthor Gender

	b/se	b/se	b/se	b/se	b/se
Experience	2030.9***	2110.5***	2086.5***	1920.4***	2105.4***
	(239.8)	(245.1)	(243.7)	(277.9)	(292.9)
Male	10694.7	6287.4	8838.2	6726.6	8708.1
	(8000.2)	(8398.2)	(7932.5)	(7940.1)	(7978.9)
$\hat{\alpha}$	17487.7***		10877.7**	11450.1***	10774.0**
	(4136.5)		(4338.3)	(4403.7)	(4402.8)
Partner $\bar{\alpha}$	23972.0**		16382.1	19074.1*	17470.7
	(10225.9)		(10692.5)	(11072.0)	(10980.7)
Male Partner $\bar{\alpha}$	-1684.3		-2775.3	-3521.3	-3018.1
	(3871.9)		(4042.1)	(4254.6)	(4223.1)
$\hat{\beta}$		22712.4***	14076.1***	13925.4***	14180.4***
		(3139.7)	(3601.6)	(3656.1)	(3693.7)
Partner $\bar{\beta}$		23142.2**	13214.1	12766.5	13091.9
		(9834.0)	(11015.9)	(11347.1)	(11377.1)
Male Partner $\bar{\beta}$		2477.8	2439.5	2733.3	2517.0
		(3772.9)	(4251.0)	(4442.3)	(4457.3)
# Total Pub.				606.0***	
				(214.1)	
Has Solo Pub.				-8782.0	-4029.5
				(6777.1)	(6882.8)
Partner Has Solo Pub.				-7783.4	-6036.9
				(15298.7)	(15157.6)
Male Partner Has Solo Pub.				1394.3	1710.0
				(13511.2)	(13422.1)
# Solo Pub.					-39.4
					(531.9)
# Duo Pub.					1255.8
					(1580.3)
Constant	175966.6***	177475.7***	170682.8***	176677.5***	173048.8***
	(8059.1)	(8569.0)	(8334.2)	(11160.4)	(11398.4)
N	4501	4501	4501	4501	4501
R^2	0.11	0.11	0.12	0.13	0.12

This table presents the effect of solo productivity and team value-added on annual earnings (in 2015 USD). Solo productivity α and team value-added β are each measured in units of one standard deviation. These standard deviations are common to the distribution of own productivity estimates as well as those of partners. Partner productivity is given as the average of solo productivity or team value-added of male and female coauthors alternatively. All specifications cluster standard errors at the author level.
*** $p < .01$, ** $p < .05$, * $p < .1$

Table 6: Coauthor Spillovers onto Own Earnings by Own and Coauthor Gender

	b/se	b/se	b/se	b/se	b/se
Experience	2024.2***	2087.3***	2061.6***	1926.7***	2102.3***
	(238.1)	(245.7)	(242.2)	(275.9)	(290.1)
Male	27816.4***	21223.9*	30455.6***	29151.9***	31265.6***
	(10562.0)	(10898.0)	(10741.0)	(10759.5)	(10742.1)
Own $\hat{\alpha}$	29595.2**		24327.6*	24401.8*	24145.4*
	(12361.8)		(13036.3)	(13106.6)	(13053.2)
Own $\hat{\alpha}$ × Male	-15542.5		-17243.8	-16837.2	-17335.7
	(13007.3)		(13712.9)	(13715.3)	(13658.8)
Partner $\bar{\alpha}$	29064.2		27112.1	31114.1	29629.2
	(29324.4)		(29733.5)	(29604.4)	(29840.8)
Partner $\bar{\alpha}$ × Male	-7406.9		-14247.0	-16439.5	-16568.4
	(31203.2)		(31779.1)	(31550.4)	(31744.6)
Male Partner $\bar{\alpha}$	-2503.9		-6217.5	-7087.5	-6643.4
	(10177.6)		(10021.9)	(10091.3)	(10192.3)
Male Partner $\bar{\alpha}$ × Male	1605.7		4542.2	5102.2	5169.0
	(10961.2)		(10911.7)	(10830.3)	(10917.9)
Own $\hat{\beta}$		28210.0***	9622.5	9905.3	9779.8
		(7673.2)	(8697.2)	(8765.6)	(8820.7)
Own $\hat{\beta}$ × Male		-6065.1	5918.7	5502.4	5937.2
		(8365.1)	(9556.2)	(9547.3)	(9618.2)
Partner $\bar{\beta}$		31490.7	20574.5	21522.7	21525.6
		(25754.5)	(26607.7)	(27415.9)	(27491.3)
Partner $\bar{\beta}$ × Male		-9209.4	-6747.5	-8628.7	-8277.6
		(27696.7)	(29123.6)	(29465.6)	(29566.4)
Male Partner $\bar{\beta}$		6887.3	3703.7	3568.0	3445.8
		(9411.2)	(9612.4)	(9967.6)	(10018.8)
Male Partner $\bar{\beta}$ × Male		-5439.3	-2014.8	-1372.7	-1468.9
		(10208.4)	(10648.6)	(10780.2)	(10833.7)
# Total Pub.				595.0***	
				(214.2)	
# Solo Pub.					-10.3
					(538.3)
# Duo Pub.					1238.1
					(1589.1)
Constant	161985.3***	165081.8***	152938.1***	159401.8***	155802.0***
	(9831.3)	(9993.9)	(9921.4)	(11931.7)	(12154.4)
Solo Pub. Controls	No	No	No	Yes	Yes
N	4501	4501	4501	4501	4501
R^2	0.11	0.12	0.13	0.13	0.13

This table presents the effect of solo productivity and team value-added on annual earnings (in 2015 USD). Solo productivity α and team value-added β are each measured in units of one standard deviation. These standard deviations are common to the distribution of own productivity estimates as well as those of partners. Partner productivity is given as the average of solo productivity or team value-added of male and female coauthors alternatively. All specifications cluster standard errors at the author level.
*** $p < .01$, ** $p < .05$, * $p < .1$

to depend on the gender of the reference author. I also allow for level differences in earnings by gender.

Controlling for experience, men earn \$20-30,000 more than women on average. I find suggestive evidence that departments reward women for solo research productivity at a higher rate but this is not statistically significant at usual levels for any specification. Interestingly, I find that men tend to receive smaller spillovers from coauthors; however, this is only statistically significant for spillovers generated by team value-added of coauthors, and only in the specification that excludes solo productivity. Allowing for gender heterogeneity also reveals the difference between own and partner value-added to be significant within genders. Partner value-added predicts significantly higher salary than does own value-added for women (p-values 0.0081–0.021) as well as for men (p-values 0.056–0.071).

Table 5 allows for heterogeneous spillovers depending on the gender of the coauthors. Average research quality of coauthored papers is not divided into three parts: the portion attributed to the reference authors, the portion attributed to female coauthors, and the portion attributed to male coauthors. Solo productivity of coauthors is divided into the portion due to female coauthors, and that of male.

I do not find compelling evidence of heterogeneous spillovers by partner gender. Male coauthors tend to spill over slightly less according to solo productivity, and slightly more by their team value-added, but these effects are statistically insignificant at usual levels for all specifications.

Finally, table 6 allows for full flexibility in the interactions between own gender and that of coauthors. None of the interaction effects yield statistically significant coefficients, providing little evidence of heterogeneous effects.

6 Conclusion

I calculate solo productivity and value-added from the universe of scholarly research output in economics. The value-added estimator effectively divides coauthored research output into portions attributed to each author based on an additive production model of research output. Previous methods of attributing credit for coauthored work assign equal credit to each coauthor, and assign credit to each author as a fixed proportion of team output. I find that coauthor value-added predicts significantly *higher* wages than does own value-added, rejecting the rule-of-thumb when it comes to salary determination.

Spillovers onto earnings generated by coauthor productivity may be due to misattribution of credit to the reference author, or to the value of professional networks. The latter could results from better outside offers available to authors who collaborate with better coauthors, or by the signal value that collaborating with better coauthors provides regarding an author's own productivity. I leave the separate identification of these channels for future work.

Crucially, the solo productivity of coauthors generates significant positive spillovers onto own earnings. This cannot be due to misattribution of credit, since the name of the reference author does not appear on those papers. These spillovers must be due to the value of professional networks, rather than misattribution.

These results provide novel insight into the value of professional networks in the academic sector, as well as new evidence that research departments negotiate salaries based on the coauthorship networks of their employees. Future work could apply similar technique to personnel data containing information on team productivity, with or without individual-level productivity measurements.

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A Robustness

The results detailed in section 5 are robust to a variety of specifications and corrections for measurement error. First I present results using the empirical Bayes shrinkage estimator, which is standard in the teacher value-added literature. I also consider baseline and Bayes-corrected estimates using log salaries as the outcome.

A.1 Log Earnings

Tables 7 to 10 recreate the baseline results using log earnings as the outcome of interest. The findings coincide closely with the baseline results.

A.2 Empirical Bayes Shrinkage Estimates

Following Helal and Coelli (2016), I generate an estimate of the productivity parameters β_i according to the following formula:

$$\hat{\beta}_i^* = \frac{\sigma_N^2}{\sigma_N^2 + \sigma_i^2}\hat{\beta}_i + \frac{\sigma_i^2}{\sigma_N^2 + \sigma_i^2}\bar{\beta} \tag{6}$$

which gives the 'shrunk' value-added estimate $\hat{\beta}_i^*$ as a weighted average of the fixed-effect estimate $\hat{\beta}_i$ and the sample mean $\bar{\beta}$. Weights are determined by the estimate of the population variance σ_N^2 and the estimated variance of each β_i parameter, given by σ_i^2. Intuitively, the Empirical Bayes formula shrinks estimates towards the mean in proportion to their variance – high-variance estimates in which we have less confidence are pulled closer towards the mean than those estimated with higher precision.

Assume that the true value-added effect of worker i is given by

$$\hat{\beta}_i = \beta_i^* + \varepsilon_i$$

where β_i^* is the fixed-effects estimate and ε_i is independent measurement error. Then the variance of the true parameter vector β^* is given by $\sigma_N^2 = var(\hat{\beta}) - \sigma_\varepsilon^2$. Estimate σ_ε^2 by the mean of σ_i^2.

Tables 11 to 14 recreate the baseline results using the empirical Bayes shrinkage estimates detailed above. I correct both solo productivity and team value-added for measurement error, and find similar results to those using the uncorrected estimates.

Tables 15 to 18 recreate the baseline results using the empirical Bayes shrinkage estimates with log wages as the outcome.

Table 7: Coauthor Spillovers onto Own Earnings

	b/se	b/se	b/se	b/se	b/se
Experience	0.0084***	0.0088***	0.0087***	0.0079***	0.0087***
	(0.00090)	(0.00092)	(0.00091)	(0.0011)	(0.0011)
Own $\hat{\alpha}$	0.066***		0.041***	0.043***	0.041***
	(0.015)		(0.015)	(0.015)	(0.015)
Partner $\bar{\alpha}$	0.078***		0.037**	0.036**	0.036**
	(0.014)		(0.015)	(0.015)	(0.015)
Own $\hat{\beta}$		0.090***	0.057***	0.058***	0.058***
		(0.012)	(0.014)	(0.014)	(0.014)
Partner $\bar{\beta}$		0.11***	0.076***	0.078***	0.077***
		(0.015)	(0.018)	(0.018)	(0.018)
Has Solo Pub.				-0.034	-0.016
				(0.027)	(0.027)
# Total Pub.				0.0022***	
				(0.00077)	
# Solo Pub.					-0.00058
					(0.0018)
# Duo Pub.					0.0066
					(0.0059)
Constant	12.1***	12.1***	12.1***	12.1***	12.0***
	(0.023)	(0.024)	(0.025)	(0.026)	(0.028)
p($\hat{\alpha} = \bar{\alpha}$)	0.61		0.85	0.76	0.83
p($\hat{\beta} = \bar{\beta}$)		0.098	0.22	0.17	0.21
N	4501	4501	4501	4501	4501
R^2	0.11	0.12	0.12	0.13	0.12

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

Table 8: Coauthor Spillovers onto Own Earnings by Own Gender

	b/se	b/se	b/se	b/se	b/se
Experience	0.0083***	0.0086***	0.0085***	0.0079***	0.0086***
	(0.00091)	(0.00093)	(0.00092)	(0.0011)	(0.0011)
Male	0.11**	0.089**	0.12***	0.12***	0.12***
	(0.043)	(0.044)	(0.044)	(0.044)	(0.044)
Own $\hat{\alpha}$	0.040**		0.033**	0.033**	0.032**
	(0.015)		(0.016)	(0.016)	(0.016)
Own $\hat{\alpha}$ × Male	-0.018		-0.021	-0.021	-0.021
	(0.016)		(0.017)	(0.017)	(0.017)
Partner $\bar{\alpha}$	0.039***		0.022	0.025*	0.024*
	(0.013)		(0.014)	(0.014)	(0.014)
Partner $\bar{\alpha}$ × Male	-0.011		-0.011	-0.012	-0.012
	(0.014)		(0.015)	(0.016)	(0.016)
Own $\hat{\beta}$		0.043***	0.015	0.016	0.015
		(0.011)	(0.013)	(0.013)	(0.013)
Own $\hat{\beta}$ × Male		-0.0093	0.0092	0.0084	0.0091
		(0.012)	(0.014)	(0.014)	(0.014)
Partner $\bar{\beta}$		0.076***	0.045***	0.046***	0.045***
		(0.012)	(0.016)	(0.016)	(0.016)
Partner $\bar{\beta}$ × Male		-0.037***	-0.018	-0.018	-0.018
		(0.013)	(0.018)	(0.018)	(0.018)
# Total Pub.				0.0022***	
				(0.00077)	
Has Solo Pub.				-0.033	-0.016
				(0.026)	(0.027)
Partner Has Solo Pub.				0.0091	0.014
				(0.056)	(0.055)
Male Partner Has Solo Pub.				-0.030	-0.030
				(0.048)	(0.047)
# Solo Pub.					-0.00052
					(0.0019)
# Duo Pub.					0.0070
					(0.0060)
Constant	12.0***	12.0***	12.0***	12.0***	12.0***
	(0.040)	(0.041)	(0.040)	(0.048)	(0.049)
N	4501	4501	4501	4501	4501
R^2	0.11	0.12	0.13	0.14	0.13

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

Table 9: Coauthor Spillovers onto Own Earnings by Partner Gender

	b/se	b/se	b/se	b/se	b/se
Experience	0.0083***	0.0086***	0.0085***	0.0079***	0.0086***
	(0.00092)	(0.00094)	(0.00093)	(0.0011)	(0.0011)
Male	0.043	0.026	0.036	0.029	0.036
	(0.031)	(0.032)	(0.031)	(0.031)	(0.031)
$\hat{\alpha}$	0.026***		0.016***	0.016***	0.016***
	(0.0056)		(0.0059)	(0.0059)	(0.0059)
Partner $\bar{\alpha}$	0.036**		0.024	0.026*	0.023
	(0.014)		(0.015)	(0.016)	(0.015)
Male Partner $\bar{\alpha}$	-0.0068		-0.011	-0.012	-0.010
	(0.014)		(0.015)	(0.016)	(0.015)
$\hat{\beta}$		0.035***	0.022***	0.022***	0.022***
		(0.0046)	(0.0054)	(0.0054)	(0.0055)
Partner $\bar{\beta}$		0.035**	0.020	0.019	0.019
		(0.015)	(0.017)	(0.017)	(0.017)
Male Partner $\bar{\beta}$		0.0100	0.010	0.012	0.011
		(0.015)	(0.016)	(0.017)	(0.017)
# Total Pub.				0.0022***	
				(0.00077)	
Has Solo Pub.				-0.032	-0.014
				(0.027)	(0.027)
Partner Has Solo Pub.				-0.0044	0.0027
				(0.060)	(0.060)
Male Partner Has Solo Pub.				-0.0100	-0.012
				(0.054)	(0.054)
# Solo Pub.					-0.00057
					(0.0018)
# Duo Pub.					0.0070
					(0.0059)
Constant	12.0***	12.1***	12.0***	12.0***	12.0***
	(0.032)	(0.034)	(0.033)	(0.043)	(0.044)
N	4501	4501	4501	4501	4501
R^2	0.11	0.12	0.13	0.13	0.13

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

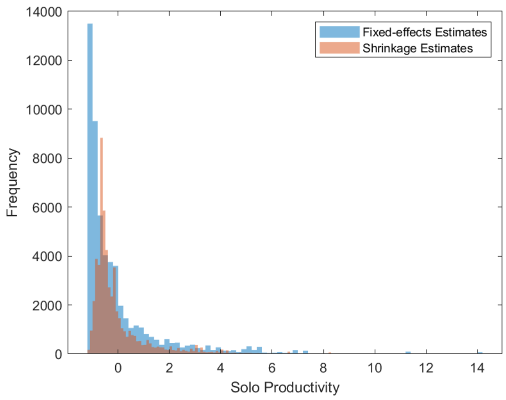
Table 10: Coauthor Spillovers onto Own Earnings by Own and Partner Gender

	b/se	b/se	b/se	b/se	b/se
Experience	0.0083***	0.0085***	0.0084***	0.0079***	0.0085***
	(0.00091)	(0.00094)	(0.00093)	(0.0011)	(0.0011)
Male	0.11**	0.086*	0.12***	0.11**	0.12***
	(0.043)	(0.045)	(0.045)	(0.045)	(0.045)
Own $\hat{\alpha}$	0.039**		0.031*	0.031*	0.031*
	(0.016)		(0.016)	(0.017)	(0.017)
Own $\hat{\alpha}$ × Male	-0.017		-0.020	-0.019	-0.020
	(0.017)		(0.017)	(0.018)	(0.018)
Partner $\bar{\alpha}$	0.044		0.041	0.044	0.042
	(0.039)		(0.039)	(0.040)	(0.040)
Partner $\bar{\alpha}$ × Male	-0.011		-0.022	-0.024	-0.025
	(0.042)		(0.042)	(0.043)	(0.043)
Male Partner $\bar{\alpha}$	-0.0055		-0.020	-0.022	-0.020
	(0.037)		(0.035)	(0.036)	(0.036)
Male Partner $\bar{\alpha}$ × Male	-0.000039		0.012	0.013	0.014
	(0.039)		(0.039)	(0.039)	(0.039)
Own $\hat{\beta}$		0.042***	0.015	0.015	0.015
		(0.011)	(0.013)	(0.013)	(0.013)
Own $\hat{\beta}$ × Male		-0.0083	0.0094	0.0086	0.0093
		(0.012)	(0.014)	(0.014)	(0.014)
Partner $\bar{\beta}$		0.047	0.031	0.031	0.031
		(0.040)	(0.040)	(0.042)	(0.042)
Partner $\bar{\beta}$ × Male		-0.013	-0.011	-0.012	-0.011
		(0.043)	(0.044)	(0.045)	(0.045)
Male Partner $\bar{\beta}$		0.029	0.016	0.017	0.017
		(0.039)	(0.038)	(0.040)	(0.040)
Male Partner $\bar{\beta}$ × Male		-0.024	-0.0086	-0.0076	-0.0082
		(0.042)	(0.042)	(0.043)	(0.043)
# Total Pub.				0.0022***	
				(0.00078)	
# Solo Pub.					-0.00047
					(0.0018)
# Duo Pub.					0.0070
					(0.0060)
Constant	12.0***	12.0***	12.0***	12.0***	12.0***
	(0.040)	(0.042)	(0.041)	(0.049)	(0.049)
Solo Pub. Controls	No	No	No	Yes	Yes
N	4501	4501	4501	4501	4501
R^2	0.11	0.12	0.13	0.14	0.13

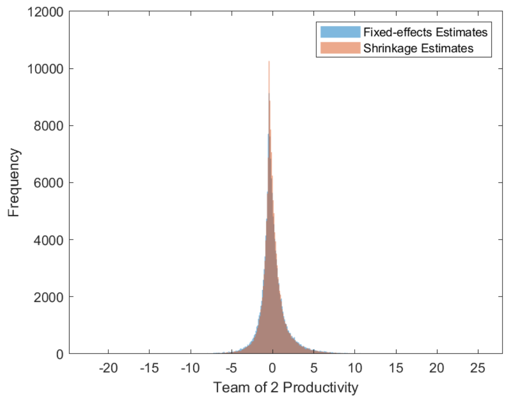
*** $p < .01$, ** $p < .05$, * $p < .1$

Figure 2: Empirical Bayes Shrinkage Estimates

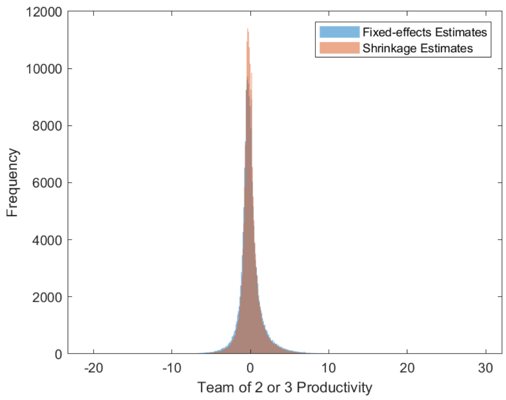
(a) Solo Productivity



(b) Value-added, Teams of Two



(c) Value-added, Teams of Two and Three



(d) All Measures

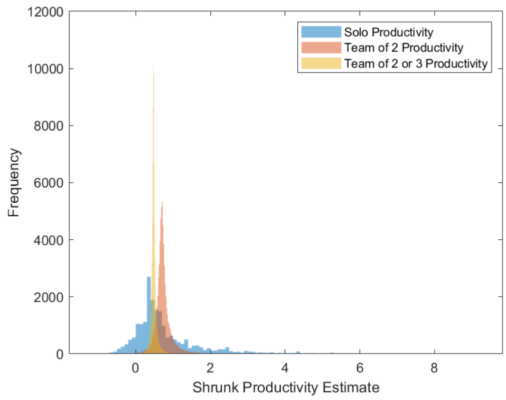


Table 11: Coauthor Spillovers onto Own Earnings

	b/se	b/se	b/se	b/se	b/se
Experience	1967.6***	2133.9***	2061.1***	1876.9***	2090.8***
	(235.4)	(239.8)	(238.1)	(271.5)	(285.4)
Own $\hat{\alpha}$	18438.8***		11974.9***	12206.9***	11830.7***
	(4175.4)		(4396.0)	(4459.8)	(4461.2)
Partner $\bar{\alpha}$	17683.3***		7407.0*	7354.3*	7324.4*
	(3615.9)		(4055.2)	(4031.0)	(4092.8)
Own $\hat{\beta}$		22843.4***	14455.7***	14597.6***	14738.0***
		(3111.2)	(3706.4)	(3771.7)	(3804.5)
Partner $\bar{\beta}$		29060.6***	19396.9***	20023.9***	19668.0***
		(3948.2)	(4713.1)	(4694.2)	(4738.5)
Has Solo Pub.				-8641.1	-3616.8
				(6839.4)	(6959.4)
# Total Pub.				561.5***	
				(215.0)	
# Solo Pub.					-151.8
					(537.2)
# Duo Pub.					1106.0
					(1574.8)
Constant	182952.8***	181414.5***	176027.8***	175955.1***	175000.8***
	(5927.8)	(5747.9)	(6210.4)	(6631.0)	(7017.7)
p($\hat{\alpha} = \bar{\alpha}$)	0.91		0.47	0.45	0.48
p($\hat{\beta} = \bar{\beta}$)		0.10	0.21	0.16	0.21
N	4501	4501	4501	4501	4501
R^2	0.11	0.11	0.12	0.13	0.12

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

Table 12: Coauthor Spillovers onto Own Earnings by Own Gender

	b/se	b/se	b/se	b/se	b/se
Experience	1935.2***	2091.7***	2014.3***	1881.8***	2068.3***
	(237.3)	(243.4)	(240.0)	(275.6)	(289.6)
Male	32213.6***	21693.3*	34042.7***	33196.7***	34985.9***
	(10855.5)	(11126.6)	(10741.2)	(10814.8)	(10774.7)
Own $\hat{\alpha}$	18016.7***		16128.3**	15997.1**	15965.5**
	(6157.2)		(6614.8)	(6681.2)	(6676.0)
Own $\hat{\alpha} \times$ Male	-10138.8		-11708.3*	-11534.5	-11651.5*
	(6548.5)		(7024.3)	(7047.3)	(7036.2)
Partner $\bar{\alpha}$	9800.1*		4868.4	5903.8	5674.4
	(5189.1)		(5749.1)	(5709.9)	(5687.7)
Partner $\bar{\alpha} \times$ Male	-885.7		-1430.4	-1872.5	-1833.5
	(5552.0)		(6158.5)	(6168.6)	(6165.6)
Own $\hat{\beta}$		11708.3***	2792.6	2918.6	2822.4
		(3120.9)	(3840.7)	(3913.3)	(3929.2)
Own $\hat{\beta} \times$ Male		-2460.1	3774.7	3577.7	3768.8
		(3415.6)	(4190.6)	(4209.7)	(4233.9)
Partner $\bar{\beta}$		20017.2***	10861.3**	11091.6**	10932.7**
		(3581.7)	(5089.0)	(5063.2)	(5076.4)
Partner $\bar{\beta} \times$ Male		-9357.1**	-3364.8	-3495.3	-3452.6
		(4015.2)	(5515.5)	(5459.3)	(5481.0)
# Total Pub.				554.9***	
				(213.1)	
Has Solo Pub.				-8279.3	-3580.1
				(6759.5)	(6879.8)
Partner Has Solo Pub.				-4076.1	-2874.7
				(14185.9)	(14023.8)
Male Partner Has Solo Pub.				-3869.9	-3076.8
				(11828.0)	(11739.3)
# Solo Pub.					-121.9
					(542.6)
# Duo Pub.					1147.2
					(1597.9)
Constant	156149.9***	163590.8***	147790.8***	153631.8***	149924.6***
	(9953.4)	(10114.8)	(9728.8)	(11919.9)	(12124.0)
N	4501	4501	4501	4501	4501
R^2	0.11	0.12	0.13	0.13	0.13

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

Table 13: Coauthor Spillovers onto Own Earnings by Partner Gender

	b/se	b/se	b/se	b/se	b/se
Experience	1939.6***	2098.5***	2029.6***	1867.3***	2063.2***
	(239.0)	(245.0)	(243.0)	(278.5)	(293.2)
Male	10402.6	6177.4	8677.8	6602.5	8609.2
	(8042.8)	(8404.5)	(7986.8)	(8000.7)	(8036.5)
$\hat{\alpha}$	9729.0***		6236.2***	6284.1***	6165.0***
	(2156.5)		(2306.8)	(2346.0)	(2348.8)
Partner $\bar{\alpha}$	11004.5**		6971.2	8482.6	7557.7
	(5155.8)		(5373.1)	(5695.2)	(5652.0)
Male Partner $\bar{\alpha}$	-2071.6		-3317.8	-4403.8	-3632.3
	(5075.7)		(5279.3)	(5714.9)	(5673.5)
$\hat{\beta}$		9382.2***	5869.3***	5814.1***	5890.3***
		(1304.8)	(1533.6)	(1562.4)	(1574.3)
Partner $\bar{\beta}$		9113.8**	5508.4	5246.2	5436.8
		(3994.2)	(4539.8)	(4664.4)	(4667.0)
Male Partner $\bar{\beta}$		3097.2	2662.2	3061.8	2726.0
		(3939.3)	(4510.1)	(4697.8)	(4704.0)
# Total Pub.				572.3***	
				(213.1)	
Has Solo Pub.				-8093.9	-3184.6
				(6848.1)	(6963.1)
Partner Has Solo Pub.				-7575.1	-5643.3
				(15686.9)	(15523.8)
Male Partner Has Solo Pub.				1483.2	1570.3
				(13978.8)	(13865.2)
# Solo Pub.					-140.1
					(535.1)
# Duo Pub.					1185.2
					(1584.0)
Constant	174393.9***	176841.3***	169258.9***	175177.4***	171112.6***
	(8298.7)	(8607.8)	(8523.3)	(11443.2)	(11667.4)
N	4501	4501	4501	4501	4501
R^2	0.11	0.11	0.12	0.13	0.12

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

Table 14: Coauthor Spillovers onto Own Earnings by Own and Partner Gender

	b/se	b/se	b/se	b/se	b/se
Experience	1939.0***	2077.0***	2010.0***	1875.7***	2061.6***
	(237.5)	(245.6)	(241.6)	(276.4)	(290.3)
Male	32123.9***	20950.3*	33621.4***	32443.9***	34372.5***
	(10878.1)	(11222.4)	(11051.1)	(11058.7)	(11033.4)
Own $\hat{\alpha}$	17844.3***		15391.0**	15151.5**	15178.5**
	(6293.9)		(6864.0)	(6945.9)	(6927.9)
Own $\hat{\alpha}$ × Male	-9943.7		-11066.0	-10827.6	-11000.0
	(6674.8)		(7272.4)	(7305.6)	(7280.4)
Partner $\bar{\alpha}$	11769.8		11720.1	14053.9	13196.2
	(15390.0)		(15366.4)	(15492.1)	(15595.5)
Partner $\bar{\alpha}$ × Male	-1693.4		-6298.3	-7518.4	-7574.0
	(16289.1)		(16335.3)	(16269.0)	(16362.3)
Male Partner $\bar{\alpha}$	-1946.1		-7179.5	-8519.4	-7855.8
	(13494.3)		(13055.5)	(13355.9)	(13477.3)
Male Partner $\bar{\alpha}$ × Male	692.3		5102.6	5921.0	6027.7
	(14508.3)		(14201.5)	(14151.0)	(14264.0)
Own $\hat{\beta}$		11428.5***	2801.3	2930.4	2836.4
		(3141.4)	(3803.2)	(3870.6)	(3888.3)
Own $\hat{\beta}$ × Male		-2236.5	3733.8	3536.0	3729.4
		(3435.4)	(4155.6)	(4173.4)	(4199.7)
Partner $\bar{\beta}$		13087.1	7984.6	8303.1	8286.0
		(10731.6)	(10581.9)	(10927.1)	(10969.5)
Partner $\bar{\beta}$ × Male		-4401.6	-2307.2	-3072.2	-2847.3
		(11492.5)	(11638.1)	(11790.0)	(11839.1)
Male Partner $\bar{\beta}$		6988.8	3494.1	3430.8	3260.5
		(10032.7)	(9947.7)	(10326.2)	(10386.3)
Male Partner $\bar{\beta}$ × Male		-4903.1	-1552.9	-904.7	-1079.8
		(10839.5)	(11066.1)	(11208.1)	(11266.0)
# Total Pub.				562.7***	
				(213.5)	
# Solo Pub.					-104.0
					(541.5)
# Duo Pub.					1154.0
					(1594.5)
Constant	156184.8***	164576.2***	148393.7***	154936.4***	151110.2***
	(9967.8)	(10278.5)	(10128.6)	(12175.6)	(12383.6)
Solo Pub. Controls	No	No	No	Yes	Yes
N	4501	4501	4501	4501	4501
R^2	0.11	0.12	0.13	0.13	0.13

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

Table 15: Coauthor Spillovers onto Own Earnings

	b/se	b/se	b/se	b/se	b/se
Experience	0.0081***	0.0087***	0.0085***	0.0078***	0.0085***
	(0.00090)	(0.00092)	(0.00091)	(0.0011)	(0.0011)
Own $\hat{\alpha}$	0.070***		0.045***	0.046***	0.044***
	(0.015)		(0.016)	(0.016)	(0.016)
Partner $\bar{\alpha}$	0.069***		0.028*	0.028*	0.027*
	(0.014)		(0.015)	(0.015)	(0.016)
Own $\hat{\beta}$		0.089***	0.058***	0.058***	0.059***
		(0.012)	(0.014)	(0.014)	(0.014)
Partner $\bar{\beta}$		0.11***	0.077***	0.079***	0.078***
		(0.015)	(0.018)	(0.018)	(0.018)
Has Solo Pub.				-0.031	-0.012
				(0.027)	(0.027)
# Total Pub.				0.0021***	
				(0.00077)	
# Solo Pub.					-0.00096
					(0.0018)
# Duo Pub.					0.0064
					(0.0059)
Constant	12.1***	12.1***	12.1***	12.1***	12.0***
	(0.024)	(0.024)	(0.025)	(0.026)	(0.028)
p($\hat{\alpha} = \bar{\alpha}$)	0.94		0.47	0.44	0.45
p($\hat{\beta} = \bar{\beta}$)		0.11	0.21	0.16	0.21
N	4501	4501	4501	4501	4501
R^2	0.11	0.12	0.12	0.13	0.12

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

Table 16: Coauthor Spillovers onto Own Earnings by Own Gender

	b/se	b/se	b/se	b/se	b/se
Experience	0.0080***	0.0085***	0.0083***	0.0078***	0.0084***
	(0.00091)	(0.00093)	(0.00092)	(0.0011)	(0.0011)
Male	0.12***	0.089**	0.13***	0.13***	0.14***
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Own $\hat{\alpha}$	0.063***		0.055**	0.055**	0.054**
	(0.021)		(0.023)	(0.023)	(0.023)
Own $\hat{\alpha}$ × Male	-0.032		-0.038	-0.037	-0.037
	(0.022)		(0.024)	(0.024)	(0.024)
Partner $\bar{\alpha}$	0.046**		0.026	0.029	0.028
	(0.018)		(0.020)	(0.020)	(0.020)
Partner $\bar{\alpha}$ × Male	-0.013		-0.014	-0.016	-0.016
	(0.020)		(0.022)	(0.022)	(0.022)
Own $\hat{\beta}$		0.046***	0.012	0.012	0.012
		(0.012)	(0.014)	(0.014)	(0.015)
Own $\hat{\beta}$ × Male		-0.0093	0.015	0.014	0.015
		(0.013)	(0.016)	(0.016)	(0.016)
Partner $\bar{\beta}$		0.080***	0.044**	0.046**	0.045**
		(0.013)	(0.018)	(0.018)	(0.018)
Partner $\bar{\beta}$ × Male		-0.039***	-0.015	-0.015	-0.015
		(0.015)	(0.020)	(0.020)	(0.020)
# Total Pub.				0.0020***	
				(0.00077)	
Has Solo Pub.				-0.030	-0.012
				(0.027)	(0.027)
Partner Has Solo Pub.				0.0092	0.014
				(0.056)	(0.055)
Male Partner Has Solo Pub.				-0.030	-0.029
				(0.048)	(0.047)
# Solo Pub.					-0.00089
					(0.0019)
# Duo Pub.					0.0066
					(0.0060)
Constant	12.0***	12.0***	11.9***	12.0***	11.9***
	(0.041)	(0.042)	(0.041)	(0.049)	(0.049)
N	4501	4501	4501	4501	4501
R^2	0.11	0.12	0.13	0.14	0.13

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

Table 17: Coauthor Spillovers onto Own Earnings by Partner Gender

	b/se	b/se	b/se	b/se	b/se
Experience	0.0080***	0.0086***	0.0083***	0.0077***	0.0084***
	(0.00092)	(0.00094)	(0.00093)	(0.0011)	(0.0011)
Male	0.042	0.026	0.035	0.028	0.036
	(0.031)	(0.032)	(0.031)	(0.031)	(0.031)
$\hat{\alpha}$	0.037***		0.023***	0.023***	0.023***
	(0.0077)		(0.0082)	(0.0083)	(0.0083)
Partner $\bar{\alpha}$	0.043**		0.027	0.029	0.025
	(0.019)		(0.020)	(0.021)	(0.021)
Male Partner $\bar{\alpha}$	-0.0082		-0.013	-0.014	-0.011
	(0.018)		(0.019)	(0.021)	(0.021)
$\hat{\beta}$		0.037***	0.024***	0.024***	0.024***
		(0.0049)	(0.0059)	(0.0059)	(0.0060)
Partner $\bar{\beta}$		0.035**	0.022	0.021	0.021
		(0.016)	(0.018)	(0.018)	(0.018)
Male Partner $\bar{\beta}$		0.012	0.011	0.013	0.011
		(0.015)	(0.017)	(0.018)	(0.018)
# Total Pub.				0.0021***	
				(0.00077)	
Has Solo Pub.				-0.029	-0.011
				(0.027)	(0.027)
Partner Has Solo Pub.				-0.0019	0.0059
				(0.062)	(0.061)
Male Partner Has Solo Pub.				-0.011	-0.013
				(0.056)	(0.055)
# Solo Pub.					-0.00096
					(0.0018)
# Duo Pub.					0.0067
					(0.0060)
Constant	12.0***	12.1***	12.0***	12.0***	12.0***
	(0.033)	(0.034)	(0.034)	(0.044)	(0.045)
N	4501	4501	4501	4501	4501
R^2	0.11	0.12	0.12	0.13	0.13

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

Table 18: Coauthor Spillovers onto Own Earnings by Own and Partner Gender

	b/se	b/se	b/se	b/se	b/se
Experience	0.0080***	0.0085***	0.0083***	0.0077***	0.0084***
	(0.00091)	(0.00094)	(0.00093)	(0.0011)	(0.0011)
Male	0.12***	0.086*	0.13***	0.13***	0.13***
	(0.045)	(0.046)	(0.046)	(0.046)	(0.046)
Own $\hat{\alpha}$	0.063***		0.053**	0.052**	0.052**
	(0.021)		(0.023)	(0.024)	(0.024)
Own $\hat{\alpha} \times$ Male	-0.032		-0.036	-0.035	-0.035
	(0.023)		(0.025)	(0.025)	(0.025)
Partner $\bar{\alpha}$	0.046		0.046	0.050	0.047
	(0.054)		(0.053)	(0.054)	(0.054)
Partner $\bar{\alpha} \times$ Male	-0.0061		-0.024	-0.027	-0.028
	(0.057)		(0.057)	(0.057)	(0.058)
Male Partner $\bar{\alpha}$	-0.00046		-0.021	-0.022	-0.020
	(0.048)		(0.046)	(0.047)	(0.048)
Male Partner $\bar{\alpha} \times$ Male	-0.0071		0.011	0.012	0.013
	(0.052)		(0.050)	(0.051)	(0.051)
Own $\hat{\beta}$		0.044***	0.012	0.012	0.012
		(0.012)	(0.014)	(0.014)	(0.015)
Own $\hat{\beta} \times$ Male		-0.0083	0.015	0.014	0.015
		(0.013)	(0.016)	(0.016)	(0.016)
Partner $\bar{\beta}$		0.051	0.032	0.031	0.031
		(0.042)	(0.041)	(0.043)	(0.043)
Partner $\bar{\beta} \times$ Male		-0.017	-0.0093	-0.011	-0.0095
		(0.045)	(0.046)	(0.046)	(0.047)
Male Partner $\bar{\beta}$		0.030	0.015	0.016	0.016
		(0.041)	(0.040)	(0.041)	(0.041)
Male Partner $\bar{\beta} \times$ Male		-0.022	-0.0069	-0.0061	-0.0070
		(0.044)	(0.044)	(0.045)	(0.045)
# Total Pub.				0.0021***	
				(0.00077)	
# Solo Pub.					-0.00083
					(0.0019)
# Duo Pub.					0.0067
					(0.0060)
Constant	12.0***	12.0***	11.9***	12.0***	11.9***
	(0.041)	(0.042)	(0.042)	(0.050)	(0.050)
Solo Pub. Controls	No	No	No	Yes	Yes
N	4501	4501	4501	4501	4501
R^2	0.11	0.12	0.13	0.14	0.13

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

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