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Gender Gap in Productivity Across Science Disciplines

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Master's Thesis

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Abstract

Persistent gaps in publication productivity between men and women have been widely studied in social and economic literature since 1984, when Cole and Zuckerman referred to this discrepancy as a 'puzzle'. Existing studies on differences in publication productivity between men and women have considered different determinants of the gender gap, which partly, but not fully, explained the "gender puzzle".

My study differs from the existing literature in terms of the coverage of the data used and the key questions asked: 1) what factors contribute to the gender gap in publication productivity between male and female scientists? 2) what institutional factors facilitate productivity of female scientists? 3) how does the size of gender gap vary across disciplines? 4) which workplaces hire more women over time?

The results of my research suggest that: 1) the size of gender gap is one-third less wide when field of specialization is controlled for; 2) women gain advantages in terms of higher productivity at larger workplaces, which cannot be explained by more stringent selection; 3) the smallest gender gap is observed in typically 'feminine' fields, such as Sociology, Medicine, and Education, while the largest gap is observed in Physics and Mathematics; 4) there is a path dependence in new female hirings, in which the presence of successful females at a workplace attracts more entrances of female scientists over time.

Abstrakt

Persistentní rozdíly publikačních výsledků mužů a žen byly důkladně prozkoumány v existující literatuře počínaje rokem 1984, kdy Cole a Zuckerman poukázali na existenci významného rozdílu. Existující studie o publikační produktivitě mužů a žen prozkoumaly řadu různých determinantů rozdílu, kdy rozdíl v produktivitě se podařilo vysvětlit pouze částečně.

Má práce se odlišuje od existující literatury daty, která využívám, a otázkami, které se snažím zodpovědět. Pokouším se zodpovědět čtyři otázky: 1) jaké faktory přispívají k rozdílné publikační produktivitě mužů a žen, 2) jaké institucionální faktory umožňují produktivitu žen ve vědě, 3) jak se liší nerovnost napříč různými obory, 4) která pracoviště najímají více žen v průběhu času.

Výsledky mého výzkumu naznačuji, že 1) rozdíl mezi muži a ženami je menší o třetinu, je-li brán v potaz obor výzkumu, 2) ženy mají výhodu ve smyslu vyšší relativní produktivity na větších pracovištích, kterou nelze vysvětlit přísnějším výběrovým procesem, 3) menší nerovnost je pozorována v typicky ženských oborech jakými jsou sociologie, medicína a vzdělání, zatímco největší nerovnost je pozorována ve fyzice a matematice, 4) existuje závislost v čase mezi přijímanými ženami, kdy přítomnost úspěšné vědkyně na pracovišti přiláká více přihlášek žen.

Project of Master Thesis

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Research question and motivation:

My aim is to explore gender differences in publication performance and investigate whether, on average and other things being equal, female scientists are less productive than their male peers. The existing researches on this topic has primarily focused on specific scientific disciplines [2,3]. However, to my knowledge, an entire population of male and female scientists across all areas of research has not been studied thus far. In this empirical study, I will use the official publication data collected at the state level in the Czech Republic, rather than selecting the sample based on any observable characteristics of scientists and their outputs.

My econometric model linking publication productivity to the gender of scientists includes control variables that can account for aspects, discussed in the literature, including entrance to the job market and co-authorship strategies more accurately, thanks to clean structure of personal identifiers in the data.

Contribution:

This study aims to contribute to the literature on gender differences in scientific productivity by conducting a large-scale cross-discipline comparison of publication performance between men and women in the Czech Republic. Compared to previous empirical studies on this topic, this study considers broader coverage of publication data in terms of scientific disciplines, as well as types and quality of outputs, thus mitigating a selection issue. Further, I will leverage the accuracy and comprehensive coverage of the data to consider more dimensions of the gender productivity gap than covered in prior literature and, thus, circumstances, under which this phenomenon may occur, can be defined.

Methodology:

The main method of the analysis will be a linear regression model with different measures of publication productivity as an output variable and gender as a main explanatory variable, followed by a set of controls. The following control variables will be included in the regression model to mitigate the omitted variable bias: year of the entrance to the job market, degree of specialization/diversification of output across disciplines, workplace and/or scientific cluster fixed effects. To account for potential differences in gender gap depending on the level of the scientific influence of outputs, I will estimate a quantile regression based on the journal ranks obtained from the external JCR database. The cross-discipline comparison will be implemented for each of broader areas of research and narrower fields fixed effects included in the regression equation.

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Introduction

Historically, opportunities in higher education have been more restricted for women than for men (Moore, 1987). According to Lewis (2020), women were intentionally excluded from higher education from the time the of University of Bologna in Italy, the first university in the world, was established. Lewis explains that the roots of gender discrimination lie in the 1377 Decree of the University of Bologna, which cruelly stated that "women are considered the weapon of the devil and the main reason of sin". It was only in the nineteenth century that women began to be allowed to enter higher education in many western societies. Today, women make up more than 50% of bachelor (BA) and master's (MA) graduates globally, though there is a large gap between the percentage of women among Ph.D. holders – 43%, and those who become researchers – 32% (Table 1). Thus, the relatively high share of women in tertiary education does not imply a commensurate presence in academic research. In literature, this phenomenon is commonly known as a "leaky pipeline" (Goulden et al., 2011; Resmini, 2016; Howes et al., 2018).

There is a strand of literature investigating gender differences in academia. For example, Dolado et. al. (2012) analyze the gender balance of top-50 economics departments, and find that the distribution of female scientists across fields in uneven. Moreover, the researchers observe a path-dependence in the fields, implying that a female scientist is more likely to work in a field with a higher initial share of women. Gender inequalities are also present in scientists' promotion to tenured ranks. Weisshaar (2017) shows that male scientists have higher probability of receiving tenure than their female colleagues. She further suggests that if a female scientist receives tenure, the department in which she works is more likely to be of lower prestige, compared to the departments of tenured male peers. In contrast, Ginther & Kahn (2006) argue that the gender gap in promotion to tenure is completely eliminated after controlling for demographic, family, employer and productivity covariates. They imply that women are less likely to receive a tenured position due to their fertility decisions. Hiwever, academic performance of a single female scientists is better at every stage than an academic performance of a single man. Different patterns in collaborations and citations are also observed between male and female authors. (Larivière et al., 2013; Mishra et al., 2018). Larivière et al. (2013) find that articles,

Table 1: Share of women (%) in higher education and research

Country	Bachelor	Master	Doctoral	Researchers
Australia	59.50	53.21	48.90	
Austria	56.81	53.23	43.98	30.06
Belgium	61.35	55.53	43.85	34.82
Brazil		55.81	54.15	
Canada	59.29	56.78	47.56	
Chile	55.22	56.65	42.63	34.43
China (People's Republic of)	54.23	50.76	39.46	
Colombia	59.05	56.91	38.36	
Costa Rica	62.90	58.50	50.56	
Czech Republic	62.56	60.03	43.71	26.77
Denmark	58.78	55.72	48.95	35.76
Estonia	64.50	61.19	48.36	42.20
Finland	59.91	60.69	51.96	33.15
France	61.66	55.16	43.89	28.29
Germany	51.14	52.64	45.18	27.88
Greece	58.94	60.49	47.43	37.82
Hungary	61.06	58.11	46.23	30.48
Iceland	66.58	68.72	59.02	46.39
India	51.80	55.91	41.39	
Indonesia	58.26	47.57	37.35	
Ireland	52.66	57.25	50.95	36.34
Israel	63.40	63.68	52.80	
Italy	58.46	57.73	50.51	34.33
Japan	46.22	34.52	30.62	16.18
Korea	50.39	51.77	37.84	20.10
Latvia	62.95	67.53	54.47	52.23
Lithuania	60.92	65.23	57.88	49.51
Luxembourg	56.78	51.44	35.56	28.08
Mexico	54.03	56.71	52.00	33.45
Netherlands	56.22	57.13	48.11	26.14
New Zealand	59.54	58.41	49.89	
Norway	62.73	56.67	50.40	38.06
Poland	65.62	66.63	56.25	38.11
Portugal	59.41	58.65	52.91	43.66
Russia	56.92	54.45	47.50	39.55
Saudi Arabia	58.30	46.83	19.73	
Slovak Republic	62.88	61.95	49.15	41.92
Slovenia	61.80	66.19	54.01	32.31
Spain	59.43	58.91	52.60	40.49
Sweden	68.10	59.82	47.85	32.63
Switzerland	48.66	48.65	44.77	34.92
Turkey	52.65	45.22	46.85	37.03
United Kingdom	57.46	59.86	46.64	38.75
United States	57.34	59.54	50.29	
Global	54.40	53.49	42.64	32.04

Source: OECD data, 2018.

in which a dominant author position is held by a female scientist are cited less often than articles in which the same position is held by a man. They also show that male scientists are more likely to engage in international collaborations (which affects citations), while female scientists are more likely to be domestically oriented.

In the 1980s, Cole and Zuckerman (1984) discovered that there is a significant difference in the publication productivity of male and female scientists. This finding was coined a "gender puzzle", and has remained largely unexplained, despite the rising importance of implementation of the equity principle at the level of state policies and institutional regulations in many countries.

Over recent decades, many studies have contributed to the debate, each providing its own perspective on puzzling evidence of the gender gap in scientific performance. There are studies which summarize historical features of gender differences in scientific careers by conducting comprehensive analyses of the longitudinal gender gap in scientific productivity across disciplines. For example, Huang et al. (2020) show that over the last 60 years the number of female scientists has increased, and the gender inequality in academic productivity has been magnified.

There are many factors that influence the individual performance of scientists, along with their innate abilities and productive efforts. Gender is a proxy for some unobservable factors that determine scientific performance, most frequently studied in economic and sociological literature. Of course, there are many other factors that influence performance measures and are correlated with gender. That is why studies on differences in publication performance between men and women have considered different additional determinants, which can partially, but not fully, explain the "gender puzzle".

In this paper, I aim to contribute to the existing studies by investigating the gender gap in academic productivity across scientific disciplines using a unique dataset. I use Czech bibliometric data on academic publications across 13 years (2007-2019), covering all scientific disciplines. The data allow me to answer gender-specific questions on the academic productivity of Czech scientists and to conduct a cross-discipline analysis.

The results of my research suggest that: 1) the size of gender gap is one-third less wide when field of specialization is controlled for; 2) women gain advantages in terms of higher productivity at larger workplaces, which cannot be explained by more stringent selection; 3) the smallest gender gap is observed in typically 'feminine' fields, such as Sociology, Medicine, and Education, while the largest gap is observed in Physics and Mathematics; 4) there is a path dependence in new female hirings, in which the presence of successful females at a workplace attracts more entrances of female scientists over time.

1 Literature review

There is a strand of existing literature, aimed to identify determinants of the gender gap in scientific performance. Each determinant is carefully studied and contributes to the explanation of the "the gender gap puzzle". However, each paper uses a different dataset and time period, and studies different fields, which makes it impossible to generalize the findings over all academia. This section reviews the most relevant and common factors described in the previous studies.

1.1 Differences in family responsibilities

Differences in family responsibilities is one the most common determinants of the gender gap in scientific performance analyzed in existing literature (Carr, 1998; Stack, 2004; Fox, 2005). For example, Carr et al. (1998) evaluate the effect of child care and other dependent care responsibilities on productivity (measured by the number of publications) and career development of male and female scientists. The authors randomly selected 24 US medical schools and conducted a survey on family responsibilities and career development. The main findings are: 1) women with children devote to professional work, on average, 5 hours less than men with children; 2) female scientists are less likely to be full professors and are more likely to be assistant professors and instructors; 3) women with children spend less time on work during weekends due to childcare responsibilities; 4) females (with or without children) spend twice as much time as men on dependent responsibilities, including elder care and care for relatives; 5) women with children are less likely to have business trips due to family responsibilities than men with children; 6) female scientists with children are less likely to receive research funding from their institutions than their male colleagues with children; 7) women with children tend to have slower career development and have lower career satisfaction. Thus, measures of scientific performance (such as publication performance) which correlate with career length reduce female participation in research, because females are more likely to have career absences.

Stack (2004) contributes to exiting studies by analyzing the effect of the number of children and their age on academic productivity of scientists. The author uses a pooled sample of men and women, in contrast to other studies, in which the samples of men and women were taken separately, from all fields in engineering and science. The researcher finds that scientists who have children aged less than 11 are more productive than their counterparts. Moreover, the author suggests that in social sciences, which contain the highest proportion of female scientists, gender is not correlated with productivity. However, women in social scientists with young children still evince lower productivity levels than their peers.

Fox (2005) explores how marriage patterns and family composition influence the productivity of scientists. The latter is measured by the numbers of papers published or accepted for publications in scientific journals. The strong advantage of the data used (survey) is that it accounts for types of publications (which helps to distinguish full papers from critiques, abstracts, comments, and etc.) and time lags (between the date of submission to a journal and a publication date). Marriage patterns distinguish between a first and a subsequent marriage, taking into account the profession of a partner, while family composition shows the age and number of children in a family. The author finds that women in a first marriage have lower productivity than women in a subsequent marriage. The researcher explains this productivity pattern by the higher likelihood of being married to a scientist in a subsequent marriage, which provides greater access to information networks, resources and funding. Moreover, the study shows that female scientists with pre-school aged children are more productive than their colleagues with no children or whose children are of school age. Fox (2005) interprets this counterintuitive phenomenon as resulting from high selectivity of female scientists in marriage, research interests, and time allocation. Particularly, selectivity in research interests and time allocation imply time devoted to research-related activities, excluding such types of work as teaching, advising graduates, serving on university committees, etc.

According to the studies discussed above, differences in family responsibilities is a relevant factor, which influences academic productivity of scientists. There is no generalized answer about the type of effect this determinant has on productivity, because of differences in the datasets and approaches used. Some findings of different studies are even contradictory, and so the effects of family responsibilities on the productivity of scientists remain a field for further research. In this study, I use a bibliometric dataset, which does not contain family-related information, so it is impossible to control for family responsibilities in my regression model.

1.2 Degree of specialization

Degree of specialization has been also shown to have a positive impact on scientific performance of academicians (Leahey, 2006). Leahey claims that the extent to which scholars are focused on one or a few subfields in their research programs is a relevant factor in research productivity. One of the main arguments that Leahey (2006) uses to support her claim is that a narrower focus on a smaller number of different topics may allow researchers to exploit economies of scale by investing less time in initial exploration of new subfields, and to benefit from established professional networks and collaboration ties in a field of specialization.

Leahey emphasizes that a numerical measure of the degree of specialization, rather than the specificity of particular research areas, can explain differences in productivity between researchers. Taking into account that male and female scientists may also specialize to different extend, differences in their productivity can be attributed to the degree of specialization.

The main contribution of this paper is its unique quantitative measure of a single-field focus constructed as an inverse index of the dispersion of specialty areas in a researcher's portfolio. The author claims that specialization as a form of professional capital can be considered a determinant of scientific productivity and, potentially, of the gender gap.

Leahey (2006) conjectures that the influence of a research focus varies across fields and, therefore, can partially or fully explain differences in productivity depending on a specific field. The author studies two fields: linguistics, where the degree of specialization is presumably more important because of stronger connections across subfields, and sociology, which is characterized by more fragmented subject matter and a larger number of isolated subfields.

To construct a sample, the author merges two parts of data: a cross-section of 20 percent of tenured and tenure-track faculty members affiliated with top U.S. research universities, and publication data in the selected fields of linguistics and sociology. Moreover, the author extracts personal information from CVs or via the web-based survey, to construct a set of control variables. In addition to the key explanatory variables – degree of specialization and gender – the author uses the following controls: a career age proxied by the number of years since the researcher earned a PhD, family status, institutional affiliation and institution prestige, prestige of the PhD-granting department, employment history measured as the number of past positions, and an indicator of receipt of research funding.

Leahey (2016) constructs the degree of specialization by using keyword descriptors. Particularly, the author composed keywords for the scientists' journal articles to define the specialization of each article. Further, she calculates the ratio ratio of the cumulative number of unique keyword descriptors to the cumulative number of publications to segregate scientists with high and low degrees of specialization.

These considerations suggest that there are stark differences in productivity between tenured and tenure-track sociologists and linguists at top universities when gender is considered as a sole determinant of scientific productivity. Controlling for the field and years of experience in a regression of publication counts on the gender dummy does not significantly change the result. At the same time, the study shows that there is a strong bivariate relationship between gender and specialization, more specifically, that women specialize less than men.

The author concludes that a specialization score reduces the role of gender on productivity, thus, proving the existence of indirect channels linking gender, specialization, and productivity. Finally, the author shows that the results hold in terms of the signs of the relations in both disciplines, though with slight differences in magnitudes of a relation.

In this study, I measure the degree of specialization for each author as the largest share of scientific outputs in a given field. This approach differs from those used by Leahey (2006) due to different construction of the dataset and the number of fields covered. Thus, the measures of specialization used in this study do not focus on specific topics, but on fields, because the dataset covers all disciplines, in contrast to the two disciplines analysed by Leahey (2006).

1.3 Probability of promotion and propensity of publishing

Mairesse and Pezzoni (2015) show that there are two further confounding factors related to gender and productivity, that may potentially explain the productivity puzzle.

First, the authors show that female scientists are less likely to be promoted in academia, conditional on age and past productivity. Since career advancement is directly linked to productivity, the authors suggest it is necessary to control for it when the relationships between gender and productivity are studied. However, they claim that career progression is endogenous to productivity, because higher rank provides more opportunities and resources to foster individual productivity and facilitates promotion to higher ranks. Thus, the probability of promotion cannot be directly used along with gender as an explanatory variable in the productivity equation. Instead, an auxiliary regression is estimated in order to predict the probability of promotion, which is then included in the main regression without the risk of endogeneity problem.

Second, the authors claim that the propensity to publish at least one article, regardless of the actual number of publications produced, can itself be a function of gender and other personal characteristics that need to be taken into account in the model relating gender to productivity. This intuition stems from the previous studies (Finkel & Olswang, 1996; Fox & Faver, 1985; Ward & Wolf-Wendel, 2004) which find that family engagements have a strong effect on scientific productivity, and that the effect is not equal for men and women – motherhood and other family duties are more likely to impede the research activity of young women, especially in the early stages of their career. To avoid the omitted variable bias problem, the authors control for such factors in the main regression of productivity on the gender of scientists. They use a similar approach as in case of the propensity of promotion and include the predicted propensity of having non-zero publication output as a separate explanatory variable in the main regression.

The data sample in Mairesse and Pezzoni (2015) consists of all French physicists active in the 2004/2005 academic year, and all their publications dating back to 1975 in journals with high scientific influence indexed in the Web of Science database. Publication data allow the authors not only to obtain the main outcome variable — a count of published articles – but also to construct various collaboration variables, which are controlled for in the main regression. Additional information about birth years and academic ranks of scientists were obtained from external sources.

The most important econometric result in Mairesse and Pezzoni (2015), which was obtained from the regression of productivity on gender, controlling for age, the predicted propensities of promotion and publishing, and various collaboration characteristics, states that female scientists are at least as productive as men. Moreover, the advantage of female physicists is increasing with age, though at a decreasing rate. Finally, by including factors separately to the main regression, the authors show that collaboration variables and the predicted propensity of promotion contribute the most to the gender productivity gap. However, the overall predictive performance of the model does not exceed 37%, which needs to be taken into account when interpreting the results.

The dataset used in this study does not contain information about the authors' career positions or their development over time. Thus, the probability of promotion cannot be included in the set of controls in my regression models. However, the data allows me to measure the authors' career age and academic experience (detailed description of the variable is provided in the section "Dataset and methodology") and, therefore, to control for academic seniority.

1.4 Discrimination in the peer review process

Discrimination in the peer review process is also one of the major obstacles discussed in the literature that may impede female scientists aiming to reach higher levels of scientific productivity. Studies from decades past to more recent works (Goldberg, 1968; Levenson et al., 1975; Paludi & Bauer 1983; Lloyd, 1990; Krawczyk & Smyk, 2016) have shown that the gender of authors is an important factor in assessments of quality.

In his highly cited paper, Goldberg (1968) indicated that women have prejudices against women. The grounds for prejudiced behavior may lie in the historical stereotype that women are inferior to men. To provide evidence that such a belief does exist, Goldberg refers to previous studies which note that women are sometimes considered irrational and emotionally unpleasant (Sheriffs & McKee, 1957) and report that female scientists of the day often felt that they needed to reject their woman's role, because intellectual achievements were considered a male preserve (French & Lesser, 1964).

Goldberg (1968) suggested that female academicians may have consciously or unconsciously considered their own gender inferior, which may have been reflected in biased evaluation of scientific outputs of other females. The author conducted an experiment to test two hypotheses: 1) women evaluate scientific outputs of men more positively than identical works, in which the author is indicated as being female; 2) in fields, which are traditionally considered "female" (e.g., nursing, dietetics), the tendency from the first hypothesis would diminish or reverse.

The author used a random sample of 140 college female students, who were the participants of the experiment. 100 students received a list of 50 professional occupations and were asked to rate the degree to which they consider each field male- or female-associated. The results showed that 2 fields were strongly considered to be female-associated (dietetics and elementary-school teaching), 2 fields were strongly considered male-associated (city planning and law), and 2 fields were neutral (art history and linguistics). Further, the researcher chose one article in each of six fields from professional literature, and combined them into two equal sets of booklets. The crucial difference in the booklets was in the names of authors - the same paper was assigned to a female name in the first set of booklets, and to a male name in the second set. Eventually, each set included half of papers written by "women" and the other half written by "men".

To test the hypotheses, 40 college female students were provided by the mixed booklets and asked to read and independently evaluate the papers critically. Goldberg (1968) did not mention the role of authors' gender in the evaluation process. Information about gender was contained only in the names of authors to whom each article was assigned.

The major results of the experiment show that 1) there is a bias by women against "female" papers, which is stronger in male-associated fields; 2) anti-female trend is, surprisingly, observed in female-associated fields, which does not support the second hypothesis. Moreover, the results showed that the papers with a "female" author were evaluated as less valuable and female authors are judged as being less competent scientists than men. Goldberg (1968) concluded that women considered themselves inferior to men in all fields due to the existence of prejudices.

Levenson et al. (1975) replicated and extended Goldberg's (1968) work to answer additional questions. Particularly, the authors conducted two independent replications (Study I and Study II) at two large state universities in the U.S.

In their Study I, the authors used a pooled sample of 134 students (55 women, 79 men) and conducted the same experiment as Goldberg (1968) - students were asked to read and evaluate six papers (which differed by the authors' names) included in booklets.

In contrast to Goldberg (1968), the results obtained by Levenson et al. (1975) show that there was no significant differences in students' evaluations when controlling for gender of the authors. Moreover, there were no significant interactions between the gender of a student, the gender of an author, and the occupation type.

Levenson et al. (1975) emphasized the need to reduce the difference between students' knowledge and the field of an article to be evaluated. Therefore, the authors conducted Study II, in which 145 (33 female and 112 male) students in a political science class were asked to grade the essay answer of a student to a political science question. Half of the reviewers evaluated an essay assigned to a female name, while the other half evaluated the same essay assigned to a male name. According to the results, there was no significant difference in evaluations based on the gender of the reviewers or the gender of the author.

To sum up, Levenson et al. (1975) did not detect an anti-female trend in evaluation process either by men or women. Vanishing of this trend may be attributed to the impact of women's liberation and increasing awareness of sexism over time.

1.5 Resource allocation and institutional support

Resource allocation and institutional support has been shown (e.g., Duch et al., 2012) to historically exhibit a gender bias. Since the amount of research resources typically needed in a given discipline is highly correlated with the publication rates of scientists, this factor is commonly considered to be a determinant of gender gap.

In their research, Duch et al. (2012) aim to reveal the gender- and discipline-specific effects of research resource allocation and relative risk in career development on publication performance of scientists. The authors build their study on bibliometric data on complete publication records of faculties in top research universities in the U.S. The study is focused on seven STEM disciplines (chemistry, chemical engineering, ecology, industrial engineering, molecular biology and psychology, material science), for which scientific impact and productivity is measured. The authors support their focus on top departments by the most high impact of scientific outputs produced there. The chosen disciplines embrace a wide range of scientific approaches - some concentrate their effort on biological systems or industrial applications, while others perform mostly computational and theoretical practices. Such differentiation in the type of scientific work implies different requirements for institutional support across the disciplines, as well as different risk profiles posed to individuals during the development of their academic career.

For better clarification, the authors compare the features of two disciplines - industrial engineering and molecular biology. In industrial engineering, most of research is computational and theoretical work. Additionally, this faculty does not train a large number of students at a time. Such features suggest that researchers from industrial engineering do not have incentives to compete for limited resources, and resource support might not be a crucial factor influencing scientific productivity. Conversely, faculties in molecular biology are focused primarily on experimental research, which requires access to specialized equipment. Such specificity provokes competition among scientists for funding and acquisition of major equipment. Hence, in molecular biology access to limited resources might be one of crucial determinants of academic success.

The first question Duch et al. (2012) answers in their empirical analysis is whether different resource requirements across STEM faculties lead to heterogeneous gender-specific publication patterns. The authors hypothesize that female scientists are likely to publish less papers than male scientists in those disciplines, where resource support and requirements are crucial for academic career success. The authors' results confirm that women have lower publication rates in disciplines with high research expenditures (e.g., molecular biology), while theory- and computational-based disciplines (e.g., industrial engineering) do not show a significant difference in publication productivity across genders.

The second issue investigated by Duch et al. (2012) is how gender- and discipline-specific effects of career risk profile influence publication performance of scientists. The authors suggest that the risk to get a faculty position for post-graduate students differs across disciplines. For example, career risk for a post-graduate student pursuing research career in chemistry is small if the goal is not met. Students will get independent academic positions on average in 6 years after their first successful publication. Those Ph.D holders, who are not interested in the development of academic career, can obtain high-paying positions in chemical industry and government. Conversely, career risk in ecology is much more higher. Post-graduate students in ecology have to wait on average 8 years before learning whether there will be an opportunity to get a faculty position. Moreover, individuals who are not interested in continuation of academic career might not be settled for job positions, which provide a significant premium comparing with academic positions. According to the aforementioned discipline-specific patterns, the authors suggest that female scientists will develop their academic career in disciplines with high-risk career profile (e.g., ecology) only if they are highly qualified and strongly confident in success. Furthermore, Duch et al. (2012) show that in high risk disciplines higher qualification of female scientists (comparing with female scientists in low risk disciplines) is reflected in higher publication impact.

The dataset used in this study does not provide information on availability of resources and institutional funding provided by each discipline. However, I control for large workplaces (detailed description of this variable is provided in the section "Dataset and methodology"), which might be considered a proxy of availability of resource allocation and institutional support.

1.6 Collaboration patterns

Collaboration patterns play important role in determining individual publication performance (Uhly et al., 2015; Jadidi et al., 2017; Eagly et al., 2020).

In their research, Uhly et al. (2015) address the question whether participation of scientists in international research collaborations is affected by a family status differently for men and women. The dataset used in this study covers information on international collaborations, provided by International Survey of the Academic Profession in 2007 of 19 countries, for the period 2004-2012. Overall, the data include 25,938 respondents affiliated with academic institutions. All individuals in the data are engaged in research – they have already coped with difficulties of attaining career position, and can be considered "elite" participants in academia. In the empirical analysis, the authors cut their sample to 10 countries [1] due to comparability issues.

Uhly et al. (2015) define the dependent variable as international research collaborations. The main explanatory variables used in the empirical analysis are gender and family status. Particularly, the authors determine partner's employment status (single, part-time employed outside academia, full-time employed outside academia, unemployed, employed in academia both part- or full-time), and number of children living at home. The researchers merge the two variables into one in their empirical analysis to investigate different patterns for men and women in the combination of these two variables. The model controls for 7 categories of disciplines (STEM sciences, agriculture, business administration and economics, humanities and arts, life and medical sciences, social and behavioural sciences), age, income, having a foreign doctoral degree, time spent abroad, and participation in national collaborations. The measure of income is standardized to an individual's annual income in U.S. dollars.

The researchers find that men are significantly more likely to participate in international research collaborations than women. Particularly, the authors suggest that engagement in international research collaborations is affected by employment status of a partner. Female scientists, whose partners are employed in academia and are working at the same field, are more likely to participate in international research collaborations than

[1] Argentina, Australia, Brazil, Canada, Finland, Germany, Italy, Malaysia, the UK, the US.

female scientists with non-academic partners. The highest rate of engagement in international research collaborations is performed by male scientists with academic partner and without children. The authors suggest that these men benefit from their gender, partner's support, and absence of family responsibilities related to child care. The researchers also observe that male and female scientists with children do not perform significantly different rates of international research collaborations.

Uhly et al. (2015) conclude that presence of children does not significantly influence women's engagement in international research collaborations. The authors suggest that existence of glass fences for female scientists might be dominantly affected by a partner's employment status.

Jadidi et al. (2017) explore gender-specific distinctions in collaboration patterns of computer scientists during the 47-year period. According to the authors, research collaborations shape innovative ideas and thus, affect careers and academic success of scientists. The researchers investigate the dynamic change of collaborations in computer science and compare the development of career success of male and female scientists over time.

The authors use the DBLP Computer Science Bibliography (the database of computer science publications in journals and conferences) to build a dynamic collaboration network. The dataset used in Jadidi's et al. (2017) study contains more than 1,5 million scientists and more than 3 million articles, which have been published within 47 years. For all authors from the data, Jadidi et al. (2017) construct a collaboration network, which includes nodes (each representing an author) and edges (representing co-authorship relation). Each edge is marked by dates which correspond to the years of publications. In their empirical analysis, the authors follow a career approach (observe scientists across different career stages). The career age is defined as the difference between the last and first publication record in the DBLP database.

The authors find that the dropout rate (number of female and male researchers who stopped publishing) of women is significantly higher than of their male peers. The researchers also show that women are less likely to continue their academic career after the year of first publication. Moreover, female scientists have smaller probabilities to enter early-career and mid-career stages and, hence, become senior scientists. Further, the authors control for the revealed differences in careers between men and women, and find that females have less publications than males. Particularly, the researchers suggest that male scientists are more productive, on average, because they have a larger number of senior authors.

Jadidi et al. (2017) show that women are on average less likely to adapt the collaboration patterns that are related with success. According to the authors, successful scientists are involved into large networks and create trustful relations by entering repeating collaborations over their career. Interestingly, female scientists, who achieved career success, exhibit similar collaborative behaviour as successful male scientists. Moreover, the researchers find that women are more likely to exhibit stronger gender homophily than men at all stages of their careers.

Although collaboration patterns have been shown to be an important determinant of the gender gap in scientific productivity, the dataset used in this study does not contain such information. However, I construct a variable reflecting academic success of female scientists. I define a successful woman as those who has at least one top-decile publication within the observed period (detailed description of this variable is provided in the section "Dataset and methodology").

1.7 Academic rank

Academic rank is another factor which correlates with gender. In their research, Van den Besselaar & Sandström, (2017) address the question whether a well-known strong correlation between number of publications and number of citations holds for high impact papers (top-cited) equally for male and female scientists.

The authors investigate a sample of Swedish researchers (extracted from a dataset on Swedish universities) to explain the gender differences in scientific productivity. The sample includes data on academic rank, last position held by authors, age, and field of research (agriculture, biology and geology, computer science/math, humanities, life sciences and medicine, psychology, sciences and engineering, social sciences). To reveal gender patterns in productivity, the authors aim to answer the following questions: 1) whether the relation between quality of publications and productivity differs for male and female scientists; 2) whether m en and women are differently distributed across the productivity classes; 3) whether academic rank, author position, and age explains differences in productivity while controlling for a field of research.

Based on the 74,000 WoS-publications of Swedish researchers for the period 2008-2011, the authors rank observed publications by received citations for each researcher from the sample. Further, the publications are categorized into Characteristic Scores and Scales 0, 1, 2, 3 (CSS) classes. Van den Besselaar & Sandström, (2017) use level CSS1 (covers 37 % most cited papers) and CSS3 (covers 3,5 % most cited papers) in the empirical part. Then, the authors assign 45,000 Swedish researchers from the sample into productivity classes: from class 1, which has one published paper within 4 years under study, to class 7, which has 32 or more published papers within the same period.

After conducting an empirical analysis, the authors provide the answers to the three main aforementioned research questions. Firstly, the researchers find that the relation between number of high impact publications and productivity is equal for male and female scientists within the predetermined productivity classes. However, there are cases when higher impact publications of women (comparing to the impact of publications of their male peers) within the same productivity class are observed in a discipline with low share of female researchers. The authors suggest that such pattern might reflect gender selection and/or gender self-selection. Secondly, Van den Besselaar & Sandström, (2017) show that men outperform women numerically in higher productivity classes. Thirdly, the authors find that men on average are older, have higher academic positions, and are more productive, which partly explains the influence of gender on productivity.

To sum up, Van den Besselaar & Sandström, (2017) conclude that women are more likely to have lower academic positions, which negatively affects their publication productivity. This, in turn, reinforces holding lower position by female scientists and explains the presence of the glass ceiling for women. Hence, the authors emphasize the importance of gender equality policies, which might help to break vicious circles for females.

2 Contribution of the study

My study differs from the existing literature in terms of the coverage of the data used and the key questions asked. The existing studies on gender differences in academia are based on survey data, which allow researchers to analyze the impact of factors that can be observed only in self-reported data on the differences in scientific productivity of male and female scientists. The other group of studies uses bibliometric data to focus on specific areas of science, such as one scientific discipline or group of disciplines (e.g., Science, technology, engineering, and mathematics – STEM).

I use Czech bibliometric data retrieved from the RIV (R&D Information System of the R&D Council of the Government of the Czech Republic) database. The retrieved dataset includes complete publication data for 13 years starting from 2007 – the earliest year[2] and ending in 2019 – the most recent year with complete publication data. The RIV database is used by Czech national authorities to distribute public funding for research activities, which creates strong reporting incentives for research institutions. Adittionally, all information on scientific outputs reported in the database is carefully checked by the R&D Council for completeness and consistency, when the same output is produced and reported by several workplaces. Thus, the bibliometric data used in this analysis cover an entire country's scientific output across all fields of science.

The retrieved bibliometric dataset includes all outputs of the following types: journal publications, conference proceedings, books, and chapters. For journal articles in the dataset, journal identifiers are matched with the JCR (Journal Citation Reports of the Web of Science) database that provides information on the level of scientific influence of journals. This information is used in my empirical analysis to segregate different areas of scientific outputs in terms of their quality and to compare patterns of publication performance observed across these segments.

The administrative dataset used in this study is unique not only because it covers the universe of scientific output of a country, but also because it does not suffer from measurement error in the publication-specific institutional affiliation (employer identity)

[2] The oldest scientific output reported in the RIV database is from 1991, but according to the search results, a systematic reporting of outputs in the database has most likely started in 2007.

of authors. On top of that, identity of all co-authors in the dataset is accurately encoded via personal identifiers assigned by the R&D Council.

Another advantage of the dataset is that it allows me to define the discipline of research specialization for each person in the dataset. This is important in that female and male scientists can plausibly specialize in different sub-disciplines and also exhibit different degrees of specialization, which, if ignored, can lead to the biased estimates of the gap in scientific productivity between men and women.

The key characteristics of the data are summarized in the table below:

Time period:	2007-2019
Number of scientific outputs:	626,066
Number of publications:	343,674 (54.9%)
Number of scientists:	104,726
Share of female scientists:	41.8%
Number of workplaces:	979
- institutes of CAS:	58 (5.9%)
- university faculties:	248 (25.3%)

While the data I use has a number of key advantages, it does not contain information on age or the stage of an author's scientific career and, therefore, does not allow me to explore gender differences in career progress and promotion, or their links to gender differences in publication performance. Similar to other bibliometric studies in the literature, I also do not observe the family status of scientists and, consequently, do not study fertility choices or control for the availability of child care, which has been shown to be one of the major determinants of the gender gap in scientific productivity.

Considering all advantages and disadvantages of the data, I aim to address the following empirical questions on the publication performance of scientists: 1) what factors contribute to the gender gap in publication productivity between male and female scientists? 2) what institutional factors facilitate productivity of female scientists? 3) how does the size of gender gap vary across disciplines? 4) which workplaces hire more women over time?

3 Dataset and methodology

The main method of my analysis is a linear regression model. I consider two separate empirical questions addressed by the following models.

First, in order to explore the gender gap in publication productivity between male and female scientists, I estimate the regression equation of the form:

$$Prod_{it} = \alpha + \beta female_i + \gamma X_{it} + \epsilon_{it}, \tag{1}$$

where on the left-hand size I use different variables $Prod_{it}$ reflecting authors' publication productivity which is measured for each author in each year. On the right-hand size of equation (2) there is a gender dummy $female_i$ followed by a set of controls X_{it}. Construction of each control variable used in this regression model is described in details below. I present empirical results for different specifications of the model (1) with different variables used as controls X_{it} and different sub-samples of authors, which allows me to compare the change in the relative size of the gender gap across specifications and evaluate the contribution of each individual factor to the difference in publication performance between men and women.

Second, I aim to answer the question of: which workplaces hire more women over time? Thus, I measure the differences in patterns of hiring female scientists across workplaces while controlling for specific institutional factors. In this part of the empirical analysis I estimate the regression equation of the form:

$$NewF_{ijt} = \beta X_{ij} + \gamma_j + \delta_t + \epsilon_{ijt} \tag{2}$$

where for each workplace i in each field of science j and time period t I measure the number of female scientists $NewF_{ijt}$, who were affiliated with a workplace i, specialized in a field j, and started to produce scientific outputs in a year t. The latter variable is used a dependent variable in the model (2). The following regressors are used as independent variables: 1) set of workplace-field-specific factors X_{ij}, including the share of female and indicator for presence of at least one female scientist with at least one publication in a top-ranked journal, which are time-invariant and are measured in the starting year of the panel; 2) field fixed effects γ_j which capture time-invariant factors commonly affecting hiring patterns of all workplaces within each field; 3) time fixed effects δ_t which capture time-variant institutional factors which do not differ across fields and workplaces, and are likely to affect hiring patterns in a whole country in a given year.

In the following subsections, I first describe the construction of a sample and two separate panels used for estimation of the models (1) and (2). Then, I describe in details the construction of dependent and independent variables used in both parts of the regression analysis. Finally, before moving to the main empirical analysis, I present general patterns observed in the data.

3.1 Panels

3.1.1 Author-year panel

For the first part of the empirical analysis I start with a publication-field-author dataset, in which each observation corresponds to a publication produced by a given author in a given field of her specialization. Using the latter dataset I construct an author-year panel. Because scientists might not have publications in every period, it is important to choose an appropriate time range – active period – for each author observed in the bibliometric data, during which her publication productivity is measured. A length of the active period for each author in the panel directly determines the number of years with zero productivity and thus affects the average productivity of an author.

I focus on a sub-sample of authors who produced at least one journal publication during the 2007-2019 period. Each author enters the panel in the year of first output (including conference proceedings, books, and chapters). To account for the left-side truncation, only those authors who produced their first output in or after 2012 are kept in the dataset. I do not aim to account for the right-side truncation explicitly by restricting the sample to only those authors who continue producing outputs up until 2019. Each author exits the panel in the year of the last output – 2019 or earlier.

In each year, the author is associated with all workplaces which were listed as her affiliations in publication records from a corresponding period. In periods with zero productivity, an author is associated with workplaces which were listed in the most recent publication record.

In order to ensure that my empirical analysis describes patterns in publication activities among authors who focus on scientific research as their main activity in academia I restrict the sub-sample of authors to those who were affiliated with the Czech Academy of Sciences or a public university. The resulting sample includes 32,200 authors.

3.1.2 Workplace-year panel

For the second part of the empirical analysis I aggregate the author-year panel described above into a workplace-field-year panel summarizing the number of female scientists newly entering a workplace[3] and specializing in a given field, and the 'role' factors as defined below for each workplace, field, and year within the 2012-2019 period. The latter panel is balanced across workplaces and time, however, each workplace enters the panel only in those fields, where its affiliates are specialized.

3.2 Dependent variables

3.2.1 Number of publications (total and in top-ranked journals)

For each author in the author-year panel I calculate the total number of journal publications[4] produced in each year during the active period, including years when no publications were produced by an author. This measure of the publication productivity is used in the baseline estimation of the model (1) outlined above.

Since the dataset used for empirical analysis consists of a specific type of scientific output – journal publications, it allows me to construct a measure of publication productivity which takes into account a level of scientific influence of publications. The latter is possible to infer based on the field-specific rankings of journals.

To distinguish between different segments of journals, I retrieve the values of the Article Influence Score (AIS) assigned to major scientific journals by the Web of Science. Journal Citation Reports (JCR) containing updated values of the AIS are released annually by the Web of Science. I use the JCR data to rank journals in each field of

[3] Institutes of the Czech Academy of Sciences and faculties of public universities.

[4] Large collaborations with more than 30 co-authors are excluded from all publication counts throughout the empirical analysis.

research (OECD classification of fields) according to their AIS values and assign field-specific quartiles to each journal in the JCR data. In case of a multidisciplinary journal I weight quartiles from different fields proportionally to the number of journals in each field and assign a weighted quartile to a journal. I merge the publication dataset with the year and field-specific rankings to distinguish between top and lower-ranked journals. About half of the journals that appear in the publication dataset can be merged with the rankings data[5].

Therefore, for each author in the author-year panel, in addition to the total number of journal publications produced in each year, I calculate the number of publications produced in the journals which rank in the top 10% (top decile) of the field- and year-specific rankings constructed based on the JCR data.

3.2.2 Number of newly hired female scientists

In the workplace-field-year panel used to explore the empirical question of: which workplaces hire more women over time, I construct an outcome variable measuring the number of female scientists who entered a workplace in a given year. I consider the year when the first output was produced as a proxy for the entrance year. The entrance into academia is always associated with a single field of author's specialization, even though the first output can be produced outside this field.

Due to the left-truncation issue, which is discussed in more details in a subsequent section devoted to construction of control variables, the workplace-field-year panel starts in 2012 and, thus, the measurement error of the outcome variable is minimized.

3.3 Independent variable

3.3.1 Gender dummy

Generally, the meaning of gender differs from the meaning of biological sex. World Health Organization suggests that gender refers to an individual's "deeply felt, internal and indi-

[5]There are several possible reasons why journals might not be listed in the JCR data. The data do not include journals in Humanities. In all other fields AIS values are assigned by the Web of Science to journals only if a sufficient amount of citation data is collected, thus 'younger' journals might not be assigned AIS values.

vidual experience of gender, which may or may not correspond to the person's physiology or designated sex at birth"[6]. In this study, I omit possible gender differences and define the gender as a dichotomy variable which represents an individual's biological sex to be consistent with most existing literature.

The gender of each author in the author-year panel was identified based on the first and last names. Specifically, I used an available online resource (Gender-API.com) to map each unique first name in the dataset to one of two genders – 'male' or 'female'. Subsequently, for those first names which are lined to both genders, gender-specific endings of last names were used to identify a gender. For example, Czech first name 'Jindra', which can be both male and female, was coded as 'female' if the last name had a suffix '-ová', which typically denotes the grammatical gender in the Czech language.

3.4 Control variables

3.4.1 Career age and academic experience

In order to control for the academic seniority of scientists, I use the year of the first output (including journal publications, books, chapters, and conference proceedings) observed in the data. Because of the left censoring of the data, I cannot distinguish between scientists who entered the academic job marker in the beginning of the time period covered by the dataset (2007–2019) and those who entered academia earlier (before 2007). Therefore, assuming that the maximum length of a zero-productivity period does not typically exceed 5 consecutive years, it is possible to identify the year of entrance to the job market and to calculate the number of years of academic experience more precisely for scientists who produced their first output in or after 2012.

3.4.2 Field and degree of specialization

In order to conduct a cross-discipline analysis, I focus on the publication performance of scientists in fields of their specialization and control for the degree of their scientific focus on specific fields of research. For this, I use information about specific fields of research (OECD classification of fields), to which individual outputs in the bibliometric dataset

[6] World Health Organization: https://www.who.int/health-topics/gender

are assigned by workplaces. I measure the degree of specialization of each scientist as a share of his/her own outputs produced in a given field. For 99% of scientists in the dataset, it is possible to identify a unique field with the largest share of outputs, which I consider the field of a scientist's specialization.

In empirical analysis I focus on a specific type of scientific outputs – journal publications – only in the fields of authors' specialization. For this I first convert the original output-level data into an output-field-author format using the personal identifiers of co-authors assigned by the Czech R&D Council. Then, I create an author-field panel by calculating the total number of outputs produced by each author and the number of outputs produced by each author in each field of research. Based on these data, I identify fields of specialization of each author and use this information to subset publication-field-authors only in fields of authors' specialization, and to construct an author-year panel.

3.4.3 Workplace size and a 'large workplace' dummy

In each scientific field, I rank workplaces (institutes of the Academy of Sciences, departments of universities, other scientific organizations) in terms of the number of affiliated scientists who specialize in a given field. I define a 'large workplace' as a one in the top 10% of the field-specific distribution of the number of affiliates specialized in a field. I use the size of workplace proxied by the number of affiliates as a separate variable as well. Both variables are time-invariant and are constructed based on the entire bibliometric database, including authors whose other variables, including career age and field of specialization, cannot be defined.

3.4.4 'Role' factors at the workplace in the entrance year of a scientist

It is important to account for the 'role' factors that may affect incentives of women, who are typically underrepresented in scientific communities at both field and workplace levels, and thus, to determine differences in scientific productivity between male and female scientists. For example, female junior scientists who recently joined an academic workplace may prefer to start working under the supervision of senior scientists of the same gender (Gaule & Piacentini, 2018). Thus, in workplaces with a larger overall representation of women and with the presence of senior female faculty members, the publication productivity of junior female scientists might be higher on average than in lower-ranked workplaces. To control for this, I construct two variables: (1) a workplace-specific share of female scientists, and (2) a dummy which is equal to one if there is at least one woman affiliated with the workplace who has produced at least one publication in a top-decile journal. Both variables are time-invariant and are specified for each scientist-workplace pair in the entrance year – the year of first publication.

3.5 General patterns in the data

In Table 2 below, I present the following summary statistics for the main variables used in the author-year panel: (1) total number of observations in the author-year panel; (2) number of observations for female scientists; (3) mean and standard deviation of a corresponding variable among female scientists; (4) the absolute size of a gender gap between male and female scientists and its p-value.

A preliminary analysis of the summary statistics suggests that there are statistically significant differences in personal and workplace characteristics of male and female scientists. Specifically, men produce on average 1.68 journal publications per year which is 20% more than the average productivity of women. The average career age of men within the 2012-2019 time period is 9% higher than that of women and is equal to 2 years. The average share of male author-year observations associated with a large workplace is 5.5% larger as compared to female author-years in the panel. It is also evident that more female scientists enter workplaces which have on average larger female representation and are more likely to have at least one female scientist with publications in the top journals.

Before including the personal and workplace characteristics to the set of controls in my regression analysis, I also inspect a common support of variables by comparing their distributions among male and female scientists. As the results suggest (Annexes), there is a significant overlap between men and women in terms of all personal and workplace characteristics which are used in a subsequent analysis of the gender gap.

Table 2: Summary statistics of the author-year panel

		Female scientists			Gender gap	
	Obs.	Obs.	Mean	SD	Coeff.	*p*-value
Personal characteristics						
Average number of publications	103,886	46,578	1.40	3.34	0.32	0.000
Career age (experience)	103,886	46,578	1.85	1.82	0.17	0.000
Degree of specialization	103,886	46,578	0.85	0.19	0.00	0.076
Workplace characteristics						
Large workplace dummy	103,886	46,578	0.21	0.40	0.01	0.007
Share of females (upon entry)	103,886	46,578	0.39	0.21	-0.18	0.000
Successful females (upon entry)	103,886	46,578	0.44	0.50	-0.06	0.000

4 Empirical results

4.1 Baseline regression

In order to evaluate the general pattern of the gender gap in publication productivity of scientists, I run three baseline regressions, which are different variations of the model (1) defined above. In the first specification, there are no controls X_{it} at all. In the second specification, X_{it} includes field fixed effects. And last but not least, in the third specification the set X_{it} includes both field and workplace fixed effects. The outcome variable for all specifications is the number of journal publications produced by an author in a given year.

Table 3: Baseline regression

	Number of publications		
	(1)	(2)	(3)
female	-0.377***	-0.233***	-0.235***
	(0.0143)	(0.0149)	(0.0149)
Constant	2.126***	2.062***	2.063***
	(0.00960)	(0.00970)	(0.00958)
Field FE	-	Yes	Yes
Workplace FE	-	-	Yes
Observations	103,886	103,886	103,878
R-squared	0.007	0.039	0.079

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The results (Table 3) show that controlling for field fixed effects (FEs) yields a significant reduction of the relative gender gap, from 17.7% to 11.3%. There are different natural field-specific frequencies of publication (e.g., in Math approximately 1 publication per 3 years, while in Economics 1 publication per year), technology of science production (e.g., lab experiments, individual research, etc.), which can influence the individual productivity of scientists. Because females are differently represented in different fields, FEs remove variation in average productivity across fields, and thus reduce the size of the observed gender gap. Finally, along with field FEs, I include workplace FEs to control for institution-level factors, such as size of workplace, availability of resources and other time-invariant factors. As a result, the estimated size of the gender gap is the same as with field FEs only – 11.3%. Since estimated size of the gender gap does not change after controlling for the workplace FEs, the results suggest that there are no segregation patterns between men and women which are stronger within specific workplaces with significantly higher productivity levels, and thus, such patterns cannot help explain the gender gap. In a subsequent analysis, I control for both the field and workplace FEs, except for regression models with time-invariant workplace characteristics.

4.2 Contribution of the workplace size to the gender gap

In another regression model, I consider model (1) defined above with a set of controls X_{it} which includes the large workplace dummy, an interaction term (female scientist at a large workplace), and field FEs. I do not control for workplace FEs in this specification due to collinearity of the large workplace dummy. In this regression model, I consider two alternative outcome variables. First, I explore the gender gap in publication productivity measured as the number of all journal publication produced by an author in a given year. After that, I focus on the publication productivity in journals with the highest (top decile) rank in terms of scientific influence.

The results of estimation of both specifications (Table 4, column 1 and 2) show that the average productivity of authors, conditional on a field of specialization, is significantly lower at large workplaces. Most importantly, the coefficient of the interaction between the large workplace dummy and female dummy is positive and statistically significant in both specifications, which implies that the relative size of the gender gap is lower at larger workplaces as compared to all lower-ranked workplaces. Specifically, the relative gender gap decreases from 11.6% to 9.6% when all publications are counted in the average productivity (Table 4, column 1), while the relative gap in the number of top decile publications decreases from 50% to 28% when large workplaces are compared to all lower-ranked workplaces (Table 4, column 2).

It is, however, not possible to provide a straightforward interpretation of the latter result, as there might be several possible reasons for it: (1) large workplaces might give a strong advantage to female scientists; or (2) large workplaces have more stringent selection process for academic staff. The latter would imply that female scientists working at larger workplaces have higher abilities and other personal characteristics that contribute to their productivity and increase their chances of working at larger workplaces. Thus, the productivity of females working at larger workplaces would still be high independently of the ranking of their workplace.

Table 4: Contribution of a large workplace to the gender gap

	Number of publications	Number of top decile publications
	(1)	(2)
female	-0.247***	-0.0441***
	(0.0166)	(0.00251)
large workplace	-0.263***	-0.0146***
	(0.0236)	(0.00357)
female × large workplace	0.0672*	0.0231***
	(0.0350)	(0.00531)
Constant	2.117***	0.0879***
	(0.0109)	(0.00165)
Field FE	Yes	Yes
Observations	103,886	103,886
R-squared	0.040	0.038

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

It is worth noting that since the large workplace dummy itself has a negative coefficient in both specifications (Table 4, column 1 and 2), it might imply that there is no statistical evidence of a more stringent selection of academics at larger workplaces in general and, thus a smaller gender gap observed at these workplaces can be explained by more favorable institutional conditions for female scientists which facilitate their research productivity. Alternatively, the stringency of selection processes might not be the same for male and female scientists and, thus there is evidence of a gender bias.

As a potential extension to this empirical analysis I suggest a more detailed exploration of the latter evidence of a relatively smaller gender gap observed at the largest Czech workplaces. For this purpose, a matching estimation technique can be used to compare female scientists working at the large and lower-ranked workplaces who otherwise have similar personal characteristics. This empirical approach can help to isolate any possible impact of personal characteristics that increases the chances of female scientists to work at larger workplaces and contribute to their research productivity. The remaining observed differences in the productivity of females working at different workplaces would most likely be explained by specific institutional conditions that may contribute to the increased research productivity of female scientists.

4.3 Contribution of experience and specialization to the gender gap

In the last regression model relating publication productivity with a gender of scientist, I consider several different specifications, where I compare the baseline specification with only the female dummy on the right-hand side of equation (1). The results (Table 5, column 1) show that conditional on a field of author's specialization, the relative size of the gender gap is around 11%. Then, I include one personal characteristic – the degree of specialization – to the set of controls X_{it} in the equation (1). As the results (Table 5, column 2) of estimation suggest, there is a negative and statistically significant relationship between publication productivity and the degree of specialization. Also, since the absolute size of the gender gap became slightly larger, if the latter specification (Table 5, column 2) is compared to the baseline specification (Table 5, column 1), it might suggest that, conditional on a field of specialization, there is negative correlation between a female dummy and a degree of specialization. Therefore, women are on average less focused on a specific field of research, as compared to men and, thus, the size of the gender gap becomes larger, once a contribution of degree of specialization to author's productivity is factored out (Table 5, column 2).

It is also important to account for potential omitted variable bias in the specification where only degree of specialization is controlled for. This bias might arise due to an indirect relationship between the degree of specialization and publication productivity through the author's career age. Specifically, the degree of specialization is likely to be smaller among authors with longer careers as their cumulative number of publications is larger and so does the likelihood of producing publications in multiple different fields.

Table 5: Contribution of experience and specialization to the gender gap

	Number of publications			
	(1)	(2)	(3)	(4)
female	-0.233***	-0.237***	-0.215***	-0.215***
	(0.0149)	(0.0148)	(0.0148)	(0.0148)
special		-1.527***	-1.290***	-1.252***
		(0.0373)	(0.0378)	(0.0396)
age			0.133***	0.133***
			(0.00387)	(0.00387)
logsize				-0.0188***
				(0.00581)
Field FE	Yes	Yes	Yes	Yes
Observations	103,886	103,886	103,886	103,886
R-squared	0.039	0.054	0.065	0.065

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In order to explore the contribution of career age along with the degree of specialization to the gender gap in publication productivity, I include the number of years since the first publication as a proxy for career age into the set of controls X_{it} in the equation (1). I do not include a squared career age to control for potential increasing and decreasing parts of the inverted-U shape of the productivity life-cycle (Sturman, 2003), since the time period covered in the dataset is too short to observe such a pattern in a sub-sample of scientists for whom it is possible to observe the year of the first publication. The results (Table 5, column 3) suggest that publication productivity is increasing with career age, and this relationship is statistically significant. Importantly, when career age is included in the regression model, the coefficient of the degree of specialization becomes smaller in absolute terms as compared to the previous specification (Table 5, column 2). Also, the size of the gender gap in the third specification is smaller, which means that male scientists have an advantage in publication experience – they tend to have on average a larger career age. Thus, the absolute size of the gender gap becomes smaller when both factors – career age and degree of specialization – are controlled for.

Finally, in the last specification of the model (1) I include the largest set of controls X_{it}, which include a degree of specialization, career age, and the size of workplace. As the results (Table 5, column 4) suggest, the publication productivity on average is negatively associated with a size of workplace conditionally on a field of author's specialization, gender of author, her career age, and degree of specialization. The coefficient of a log-transformed size of workplace shows that a 1% increase in a size of workplace is on average associated with a decrease in the number of publications produced by an author in a given year by 0.018 which is about 1% of the average productivity of all scientists in the dataset. It is evident from the estimation results that the size of workplace itself does not contribute to the overall predictive power of the model (1). Also, the absolute size of the gender gap does not change when the size of workplace is controlled for. However, adding this factor to the specification makes the coefficient of a degree of specialization smaller in absolute value, which might suggest that scientists affiliated with larger workplaces are on average more specialized. Thus, part of the negative relationship between a degree of specialization and publication productivity was driven by an indirect channel going through the size of workplace.

4.4 Cross-discipline comparison of the gender gap

In this subsection I explore the differences in the gender gap in publication productivity across scientific disciplines. For this purpose I estimate the baseline regression model (1) with a total number of publications as a dependent variable and a gender dummy as an independent variable, separately for each discipline. I control for workplace fixed effects in the regression. I consider both a broad structure of fields (Agricultural, Engineering, Medical, Natural, and Social sciences) and narrower fields of research (OECD classification) which were previously considered in this empirical analysis as fields of authors' specialization.

After estimating the coefficient β of the female dummy in the equation (1), I calculate the percentage size of the gender gap in publication productivity between men and women by dividing the coefficient β by the intercept α. The estimated coefficients, their standard errors, and the percentage size of the gender gap are reported in Table 6 below. Additionally, in order to illustrate a weighted contribution of each field to the nation-wide level of the gender gap, I include the share of scientists specialized in each field in the results. Because for nearly every author in the dataset it was possible to identify a unique field of specialization, all shares in the last column of Table 6 can be summed up and their total sum is close to 100%[7]

The results suggest that the smallest gap among broad fields of research is observed in Engineering and Technology – in this field, male scientists produce on average only 6% more journal publications than female scientists. However, it is also true that this field is characterized by the lowest level of female representation – 33%. Therefore, this finding might suggest that there is a stronger selection of female scientists in Engineering and Technology field, which implies that women who succeed in entering this field of science are on average more productive than women working in other fields. Even though there is generally a small gender gap in Engineering and Technology, narrower disciplines within this field are rather heterogenous in terms of the size of the gender gap. For example, in Environmental biotechnology female scientists are on average 47% less productive than male scientists and this difference is statistically significant. However, in other subfields of Engineering and Technology, such as Industrial biotechnology, Materials engineering, Mechanical engineering, Medical engineering, and Nano-technology, the gender gap is not significantly different from zero, and it is not possible to reject the null hypothesis of no productivity gap between men and women. Each of these subfields represent very small shares of all authors in the country and, thus, the estimated percentage differences are rather unreliable.

[7]The total sum is not equal to 100%, because the reported results exclude Humanities.

Table 6: Cross-discipline comparison of the gender gap

Field	Coeff.	SD	Gap	Share of field
Agricultural and veterinary sciences	**-0.303*** **	**(0.056)**	**18.57%**	**4%**
Agricultural biotechnology	0.682	(0.571)	75.86%	0%
Agriculture, Forestry, and Fisheries	-0.399***	(0.069)	24.09%	3%
Animal and Dairy science	-0.218	(0.16)	13.08%	1%
Veterinary science	-0.053	(0.127)	3.78%	1%
Engineering and Technology	**-0.07*** **	**(0.03)**	**5.7%**	**13%**
Chemical engineering	-0.324**	(0.141)	22.31%	1%
Civil engineering	-0.081*	(0.047)	8.54%	3%
Environmental biotechnology	-0.876*	(0.454)	47.21%	0%
Environmental engineering	-0.294***	(0.098)	25.55%	1%
Industrial biotechnology	0.29	(0.277)	33.64%	0%
Materials engineering	0.06	(0.073)	3.71%	3%
Mechanical engineering	-0.006	(0.088)	0.52%	2%
Medical engineering	-0.061	(0.147)	6.08%	0%
Nano-technology	-0.337	(0.254)	20.29%	0%
Other engineering and technologies	-0.194**	(0.077)	15.47%	2%
Medical and Health Sciences	**-0.312*** **	**(0.032)**	**17.6%**	**18%**
Basic medicine	-0.258***	(0.049)	15.03%	5%
Clinical medicine	-0.335***	(0.047)	18.01%	10%

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Field	Coeff.	SD	Gap	Share of field
Health sciences	-0.354***	(0.08)	22.05%	3%
Medical biotechnology	0.167	(0.209)	13.85%	0%
Other medical sciences	-0.842**	(0.333)	44.58%	0%
Natural Sciences	**-0.463*** **	**(0.054)**	**23.86%**	**38%**
Biological sciences	-0.375***	(0.025)	22.13%	15%
Chemical sciences	-0.684***	(0.06)	33.42%	8%
Computer and information sciences	-0.012	(0.047)	1.68%	3%
Earth and related environmental sciences	-0.131**	(0.055)	9.3%	4%
Mathematics	-0.344***	(0.078)	26.27%	2%
Physical sciences	-1.049***	(0.361)	28.49%	6%
Social Sciences	**-0.139*** **	**(0.018)**	**13.15%**	**18%**
Economics and Business	-0.084*	(0.044)	7.79%	4%
Education	-0.153***	(0.039)	16.47%	3%
Law	-0.162***	(0.055)	14.36%	2%
Other social sciences	-0.085	(0.094)	7.7%	1%
Political science	-0.227***	(0.04)	21.38%	4%
Psychology and cognitive sciences	0.06	(0.083)	5.25%	2%
Social and economic geography	-0.215***	(0.083)	21.29%	1%
Sociology	-0.076*	(0.046)	7.67%	2%

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The second smallest gap is associated with Social Sciences, where men produce on average 13% more journal publications than women. This field is characterized by a high level of female representation – 53% of all scientists specialized in this field are women. Therefore, it is unlikely that in Social Sciences a relatively small gap in publication productivity is driven by a strong selection, as I conjectured above. At the same time, similarly to Engineering and Technology, Social Science disciplines exhibit very different magnitudes of a gender gap. For example, the estimates of the gender gap range from 8% in Economics and Business to 21% in Political science. Both of these disciplines have a high level of female representation – around 45% – and each of them represent around 4% of all scientists in the country.

According to the field-specific regression outputs reported in Table 6, the largest gap among broad fields of research is observed in Natural Sciences, even after controlling for institutional factors captured by the workplace fixed effects. The estimated percentage gap in this field is almost 24%. It is also important to note that similarly large productivity gap is observed in disciplines within Natural Sciences, including Biology and Chemistry, which constitute a relatively large share of all scientists in the Czech Republic. The publication productivity in these fields is on average 22-33% higher among male scientists as compared to female scientists. Last but not least, since female representation in Biology and Chemistry is rather large, ranging from 50% to 60%, it is important to explore specific factors contributing to the large size of the gender gap in these fields, which I discuss as a potential extension in the following section of this study.

In order to extend the cross-discipline analysis of the gender gap, I explore the relationship between the gap in publication productivity and the level of female representation across disciplines. Graphical representation of this relationship, which is depicted in Figure 1, allows me to mark several clusters of disciplines with similar patterns. One group of disciplines located on the south-west part of the graph – Engineering disciplines – is characterized by low female representation and low gender gap, which can be explained by a stronger selection of women into these disciplines. Another group on the north-west have similarly low levels of female representation, but in contrast to the previous group, it exhibits extremely high levels of gender gap (ranging between 28-30%). Such disciplines – Physical sciences and Mathematics – are perceived to be 'masculine' fields both due to low female representation and to significant differences in productivity of male and female scientists. There is a larger group of disciplines clustered in the middle part of the graph which can be characterized as 'gender-balanced', with a productivity gap ranging from 8% – in Economics and Business – to 30% – in Chemistry and Biology. In such fields a large variation in the gender gap, provided that the representation of both genders is equal, might be driven by different technologies of knowledge production and, thus different typical sizes of teams on the one hand, and different patterns in a scientific team-formation potentially leading to different magnitudes of gender homophily on the other hand. The conjecture, however, remains outside the scope of this empirical study and I discuss it only briefly in the following section dedicated to potential extensions of this study. Finally, there is yet another group of disciplines clustered on the south-east part of the graph with exceptional levels of female representation which are also characterized by a relatively relatively small gender gap. Such fields – Sociology, Education, and Medicine – are commonly known as 'feminine' fields and are contrasted to the 'masculine' fields mentioned above.

4.5 The gap across workplaces in female productivity

In the following part of the empirical analysis, instead of comparing publication productivity of men and women, I focus only on female scientists and I explore specific institutional factors which might impact their publication productivity. First, I consider a specification of the model (1) described above, where the number of publications, irrespective of their scientific influence, produced by an author in a given year is related to the following factors: (1) whether the workplace is ranked in the top 10% of the field-specific distribution of the number of affiliates specialized in a field; (2) share of females at the workplace in the year of female scientist's entrance to academia; (3) whether there was at least one senior female scientist with a publication in a top decile journal when a scientist entered academia. In an alternative model I use a different performance measure – the number of publications in top-ranked journals. Both specifications control for field FEs and, thus, allow me to pose a question of whether women are more productive relative

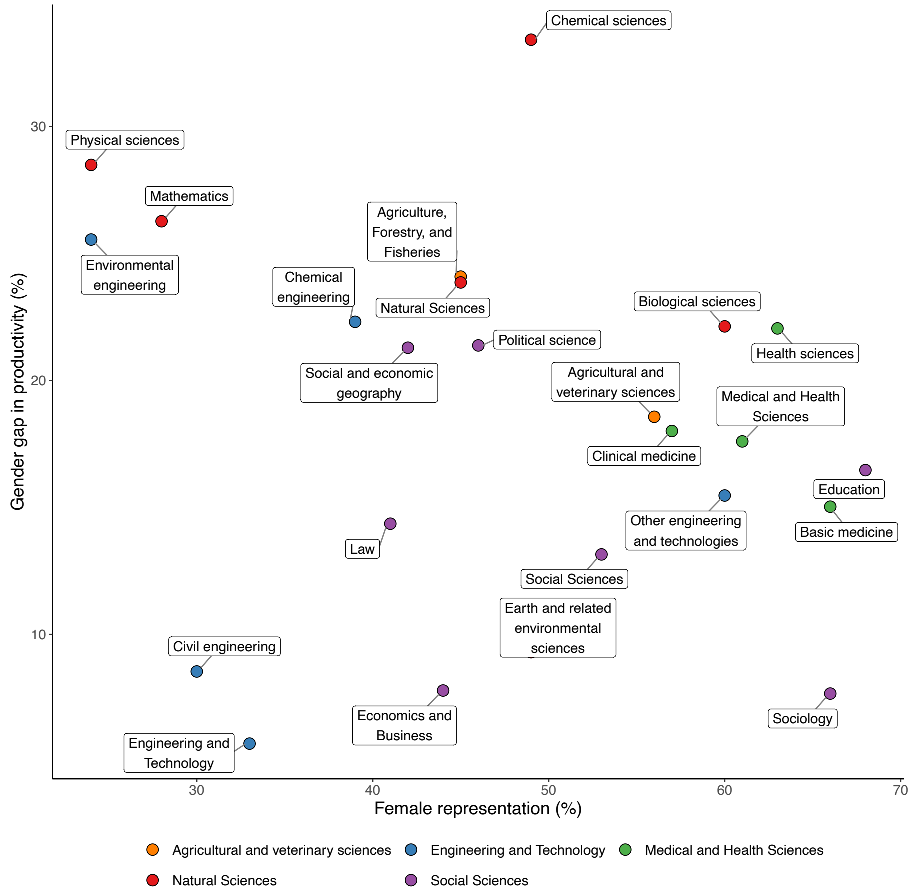

Figure 1: Gender gap in productivity and female representation

to other women in the same field, when they work at larger workplaces, or at workplaces with larger female representation, or at workplaces where there is at least one successful female scientist.

The results of estimations presented in Table 7 show that when specific 'role' factors are controlled for in the regression, there is no evidence of female scientists being more productive at larger workplaces anymore. It is also evident from the estimated coefficients that, conditional on field of author's specialization, the number of all and top decile publications produced in a given year is positively associated with the presence of at least one female scientist with publications in top-ranked journals at the workplace at time when a female author entered academia. However, higher female representation at the workplace in the entrance year exhibits a statistically significant association with publication productivity only in the case when all publications, irrespective of their scientific impact, are counted (Table 7, column 1).

Table 7: The gap across workplaces in female productivity

	Number of publications	Number of top decile publications
	(1)	(2)
top workplace	0.0390	0.00184
	(0.0343)	(0.00474)
share female enter	0.612***	0.00361
	(0.0654)	(0.00904)
success female enter	0.135***	0.0437***
	(0.0268)	(0.00371)
Field FE	Yes	Yes
Observations	46,571	46,571
R-squared	0.115	0.063

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.6 Differences in hiring of female scientists across workplaces

The last question I aim to answer in this study is: which workplaces hire more women over time. The regression model (2) described above aims to address this question. This model relates the number of new female hirings by a workplace in a given year and field to institutional factors $X_i j$, as well as field FEs γ_j and year FEs δ_t.

In the first specification of this model, the set of controls X_{ij} includes only the initial (2012) share of females at a workplace. The results provide statistically significant results (Table 8, column 1), which means that there might be a general pattern of 'path dependence' in female hiring. That is, workplaces with larger female representation also tend to hire more women over time.

The second specification of the model (2) controls for the presence of senior females at a workplace (Table 8, column 2), which has a positive and statistically significant effect on the number of newly hired female scientists. Thus, the probability of new hirings of female scientists is higher at workplaces where the work environment is more favorable for women. Moreover, workplaces with prominent female faculty attract more female entrants over time.

Finally, in the last regression specification, on top of the factors which were controlled

Table 8: Workplace environment and entrance of new female scientists

	Number of new female scientists		
	(1)	(2)	(3)
share of females	0.269***	0.111	0.162**
	(0.0902)	(0.0779)	(0.0732)
presence of successful females		1.207***	1.042***
		(0.0121)	(0.0117)
large workplace			7.235***
			(0.276)
share of females X large workplace			6.353***
			(0.728)
Year FE	Yes	Yes	Yes
Field FE	Yes	Yes	Yes
Observations	28,795	28,795	28,795
R-squared	0.101	0.331	0.410

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

for above, I include the indicator of a top workplace and its interaction with the share of females at a workplace to the set of controls X_{ij}. The results (Table 8, column 3) suggest that larger female representation has a much stronger association with the number of new hires at larger workplaces – an additional 1% of females translates into 6.5 more newly hired females at larger workplaces, whereas at lower-ranked workplaces this number is almost 40 times smaller.

5 Potential extensions

This study is based on a bibliometric dataset retrieved from the RIV database. Bibliometric data do not contain information about family responsibilities, partner's economic status, career position, etc., which could help explain the gender gap in publication productivity of scientists. Moreover, since the data contain information only about published outputs (conditional on successful selection), it was not possible to explore patterns of discrimination in my empirical analysis. These deficiencies can be potentially resolved by conducting an experimental study and collecting necessary data by surveying subjects.

Therefore, one potential extension of my study can be a follow-up research based on a more comprehensive dataset, which would combine information on a wider range of potential determinants of the gender gap. However, since conducting a large-scale experimental study and collecting personal information via surveys for a large sample of scientists might not be feasible, I consider manual collection (web scraping) of supplementary data for a random sub-sample of authors who are currently present in the bibliometric data.

While a follow-up research requires collection of additional data, there are several potential extensions discussed in this study which can be implemented using the present bibliometric dataset. First, it was found in this study that female scientists might have an advantage in terms of higher publication productivity when they work at larger workplaces. It can be possible to verify whether the latter finding still holds if a matched sample of female scientists with similar personal characteristics is considered. Second, it was found in a cross-discipline comparison of the gender gap in publication productivity that there are scientific fields with a similar level of female representation, but different relative sizes of the gender gap. Potential reasons for this pattern is an important question which can be addressed in a follow-up study. In this study, it was not possible to explain such differences across fields by available personal characteristics of authors. However, it might be possible that there specific patterns in a scientific team formation driven both by a female representation and by gender-specific preferences of working with the same gender, which result in 'sub-optimal' sizes of teams dominated by women. Such allocation of scientists into scientific teams might indirectly and unevenly depreciate their productivity, thus, explaining larger sizes of the gender gap in fields with different typical sizes of scientific teams. The exploration of gendered patterns of a scientific team formation and of a gender homophily observed across fields of research can be considered as another potential extension of this work.

6 Conclusion

Even though females may have equal access to higher education, they remain underrepresented in academia. The existing studies consider various determinants of the gender gap in publication performance, but they do not fully explain the gaps between male and female scientists. Moreover, existing studies are mostly based on survey (self-reported) data, or bibliometric data in selected disciplines or areas of science.

In this study, I use a comprehensive bibliometric dataset, which covers the publication performance of the entire population of Czech scientists. In the regression models, the dependent variables are defined as number of publications, and number of newly hired female scientist. The gender is the main explanatory variable, followed by the set of controls: career age and academic experience, field and degree of specialization, workplace size and a "large workplace" dummy, "role" factors at the workplace in the entrance year of a scientist. The advantages of the data also allow me to conduct a comprehensive cross-discipline analysis of the gender gap in publication performance of scientists and to investigate the hiring patterns of Czech workplaces with respect to male and female scientists.

The results of my research suggest that: 1) the size of gender gap is one-third less wide when field of specialization is controlled for; 2) women gain advantages in terms of higher productivity at larger workplaces, which cannot be explained by more stringent selection; 3) the smallest gender gap is observed in typically "feminine" fields, such as Sociology, Medicine, and Education, while the largest gap is observed in Physics and Mathematics; 4) there is a path dependence in new female hirings, in which the presence of successful females at a workplace attracts more entrances of female scientists over time.

While the dataset used in this study has a number of advantages, it does not contain information about family responsibilities, partner's economic status, career position, etc., which could help explain the gender gap in publication productivity of scientists. These deficiencies can be potentially resolved by conducting an experimental study and collecting necessary data by surveying subjects. Therefore, one potential extension of my study can be a follow-up research based on a more comprehensive dataset, which would combine information on a wider range of potential determinants of the gender gap.

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Annexes

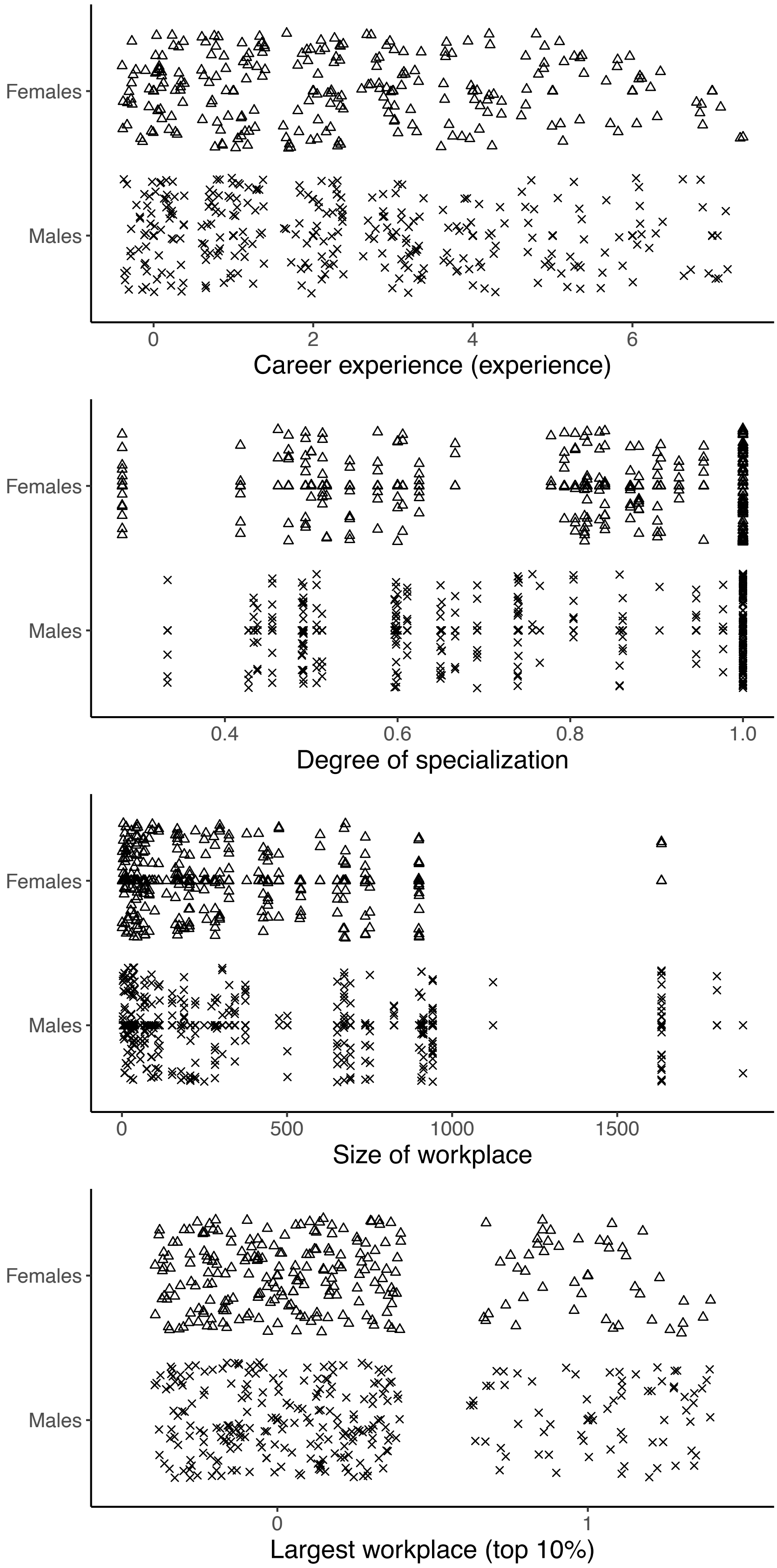

Figure A.1: Common support of control variables