Investigating writing style as a contributor to gender gaps in science and technology*

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Abstract

A growing stream of research finds that scientific contributions are evaluated differently depending on the gender of the author. In this article, we consider whether gender differences in writing styles—how men and women communicate their work—may contribute to these observed gender gaps. We ground our investigation in a framework for characterizing the linguistic style of written text, with two sets of features—informational (i.e., features that emphasize facts) and involved (i.e., features that emphasize relationships). Using a large sample of academic papers and patents, we find significant differences in writing style by gender, with women using more involved features in their writing. Papers and patents with more involved features also tend to be cited more by women. Our findings suggest that scientific text is not devoid of personal character, which could contribute to bias in evaluation, thereby compromising the norm of universalism as a foundational principle of science.

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1 Introduction

In his classic essay, “The Normative Structure of Science,” sociologist Robert K. Merton identified universalism as a foundational principle of the scientific enterprise, one that distinguishes science from other competing systems of knowing. According to Merton and Storer’s formulation (Merton and Storer, 1973, p. 270), universalism holds that the evaluation of scientific contributions “is not to depend on the personal or social attributes of their protagonist; his race, nationality, religion, class, and personal qualities are as such irrelevant.” The value of universalism is manifested perhaps most concretely in the practice of double-blind peer review, wherein the identities of both those making scientific claims and those evaluating them are obscured from one another (Bornmann, 2011).

While scholars have long observed that adherence to the principle of universalism is far from universal (Mulkay, 1976; Cole, 1992; Long and Fox, 1995), the growing availability of large-scale databases is creating opportunities for unprecedented insight into processes of scientific evaluation (Teplitskiy et al., 2018; Dondio et al., 2019; Lane et al., 2021), including the barriers that inhibit objective assessments. Recent literature in particular has raised considerable concern about the role of gender in scientific evaluation (Moss-Racusin et al., 2012; Reuben et al., 2014; Oliveira et al., 2019; Card et al., 2020a). There is growing evidence to suggest that the contributions of women are devalued relative to men (Joshi, 2014; Sarsons, 2017; Vásárhelyi et al., 2021; King et al., 2017; Ni et al., 2021), thereby undermining the imperative of universalism, and ultimately weakening the scientific enterprise by suppressing diverse perspectives. Prior work has shown, for example, that relative to men, women’s contributions are awarded less grant funding from prestigious sponsors (Oliveira et al., 2019; Kolev et al., 2020), less likely to be granted patent protection (Jensen et al., 2018), and also receive fewer citations from other academic papers (Larivière et al., 2013). These gaps appear to be driven at least in part by homophily, as men tend to cite other men over women, even in fields with higher female representation, such as the social sciences (Potthoff and Zimmermann, 2017; Dion et al., 2018; Ghiasi et al., 2018). Men also tend to self-cite at a much higher rate than women (King et al., 2017).

Yet much remains unknown about the role of gender in scientific assessment. Prior scholarship has highlighted differences in field, topic choice, or research quality as playing an important role in explaining observed gaps between men and women (Leahey, 2007; Key and Sumner, 2019). While these factors are undoubtedly important, studies have also shown that even when accounting for field, topic choice, and quality, men’s and women’s research is evaluated differently (Hengel, 2017; Hengel and Moon, 2020). Studies further report gender gaps even in the presence of double-blind review (Kolev et al., 2020; Mahajan et al., 2020), suggesting that conscious or unconscious bias based on the identity of the author is likely not the determinative factor (van der Lee and Ellemers, 2015; Hospido and Sanz, 2019; Card et al., 2021, 2020b).

In this article, we aim to contribute to the systematic understanding of gender differences in the evaluation of scientific and technical work using a linguistic lens. Specifically, we draw on a prior framework, developed by Biber (1988), which contrasts linguistic features characteristic of a high information density (“informational” features) with linguistic features associated with more affective, interactional content (“involved” features). This framework allows us to take a systematic approach to feature selection and also to examine features which have been overlooked as indicators of variation in the previous literature on gender gaps, such as the use of determiners or pronouns. Biber (1988) found in a corpus of epistolary writing that women used more “involved” features (e.g. increased use of pronouns) for the purpose of building a
relationship with the audience, while men used more “informational” features (e.g. increased use of cardinal numbers in texts) for the purpose of conveying the factual information. Using this framework, we conduct a large-scale analysis of gender differences in scientific and technical writing, leveraging two distinctive document types—academic articles and patented inventions—which collectively span all major fields of science and technology.

Several noteworthy findings emerge from our study. We document that even in such restricted genres as academic writing and invention descriptions, female authors tend to use more “involved” features than male authors, a pattern that holds across all scientific fields and patent subcategories. In the patent data specifically, we find that the gender of the lawyer appears to have more impact on the writing than the gender of the inventor, suggesting both the importance of attorneys in crafting patent text and the universal nature of the patterns we observe, even across individuals with very different professional training. Finally, we show that work that uses a higher number of “involved” features is more likely to be cited by female authors.

Our study builds on, but also extends, a small but growing stream of research in the Science of Science on gender and language (c.f., Fortunato et al., 2018). First, while existing literature has identified a number of differences in men’s and women’s scientific writing (Lerchenmueller et al., 2019; Kolev et al., 2020; Kim et al., 2022), the choice of features have not been motivated by a linguistic framework, thereby complicating the interpretation of the results and making comparisons across studies difficult. Second, existing research has been done within particular fields and on particular kinds of text (e.g., scientific papers), and therefore little is known about whether the patterns observed thus far will generalize across diverse fields and document types (such as patent data), which have diverse norms.

Our study also adds to the linguistics literature. First, previous research on gender differences in language utilization has largely been done on informal or conversational text, typically focusing on speech patterns, and using corpora like emails (Thomson et al., 2001), essays (Mulac et al., 2006), social media (Garimella and Mihalcea, 2016), blogs (Pennebaker, 2011). There has been far less research on gender differences in formal writing, and the work that has been done has relied on relatively small samples (Argamon et al., 2003; Biber, 1988). Second, we study a new source of text data—patented inventions—that has not been studied in previous linguistic analyses. Patents represent a more restricted genre in terms of stylistic expression than academic papers, therefore, finding stylistic differences by gender is especially notable.

2 Results

2.1 Data Overview

We conduct the analysis on two datasets: abstracts of academic papers from Web of Science\(^1\) and abstracts of patents from PatentsView\(^2\). For the purposes of our study, we narrow our focus to solo-authored papers and patents (i.e., we exclude papers and patents written by teams). In the patent data, we also narrow our sample to include only those inventors with a single lawyer, in order to more cleanly control for the gender of the lawyer, as lawyers are frequently involved in the writing and editing of patent text. In total, we use 256,260 publications and 16,053 patents in the analysis. Additional details on the dataset construction can be found in the Materials and Methods section.

\(^{1}\)Web of Science: https://clarivate.com/webofsciencegroup/solutions/web-of-science/

\(^{2}\)PatentsView: http://www.patentsview.org/
For each paper and patent in our sample, we construct a series of measures tracking the utilization of informational features (using past tense, determiners, and cardinal numbers as indicators) and involved features (using pronouns, questions, and non-phrasal coordination (“and”) as indicators). Figure 1 gives an overview of the specific features of interest as well as more details about the computation of these features. We define three separate measures: involved rate, informational rate, and Involved-Informational Ratio. Because our corpus includes academic writing and invention descriptions, there is already a high utilization of informational features; therefore, in addition to involved and informational rates, we are also interested in seeing the relative rate at which writers use involved features in relation to informational features (Involved-Informational Ratio). More information on the developed measures is included in the Materials and Methods section.

Figure 1. Involved and informational linguistic features and calculations. (A) This panel specifies the involved and informational features used in our analysis and displays the formulas used to calculate the involved rate, the informational rate, and the involved-informational ratio. (B) This panel presents two example texts; one authored by a female and the other by a male. The features are highlighted, with colors corresponding to those denoting the features in panel A. On the right-hand side, the involved rate, informational rate, and involved-informational ratio are calculated for the texts displayed on the left-hand side.

### 2.2 Writing Examples

Before presenting our quantitative results, we first highlight several examples from our data that illustrate the differences between the informational and involved styles. Beginning with papers, consider the following excerpts from two abstracts, one written by a female author and the other written by a male, both published in the same field (Business & Economics), during the same time period (1990s).

**Female writing sample**

Why do companies in the United Kingdom pay scrip (i.e., in stock) dividends? Are tax savings the sole motive for this option? If so, are all tax-loss companies offering this option? Or is this option driven by other motives, such as cash savings, signaling, and agency conflicts? In this study, I provide some insights into the motivation for scrip-dividend payment by comparing the operational performance and other characteristics of all companies that distributed scrip dividends with those of a control group of non-scrip-paying, but otherwise

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We also released an open-source Python package to compute these linguistic features, available here: [https://pypi.org/project/stylometer](https://pypi.org/project/stylometer).
similar firms. Scrip dividends are offered by an increasing number of companies in the United Kingdom as an option whereby shareholders are able to choose between receiving dividends in cash or the equivalent in the form of shares (scrip). Companies stress tax savings when they offer this option because, unlike cash dividends, the scrip option is not subject to a payment of the advanced corporation tax (ACT).

(2) The rich variety of securities innovations in recent years continues to intrigue academicians and practitioners alike. The array of innovative securities includes a variety of equity-linked debt securities. On January 28, 1991, the Republic of Austria publicly offered $100 million principal amount of a new equity-linked debt security called stock index growth notes (“SIGNs”) in the United States. The SIGNs were scheduled to mature in approximately 5.5 years. They would make no payments of interest prior to maturity. If the value of the S&P 500 is below 336.69 on the maturity date, the holder will receive $10, the initial offering price. If the value exceeds 336.69, the holder will get $10 plus $10 multiplied by the percentage appreciation in the S&P 500 above 336.69. SIGNs may thus be characterized as a package consisting of (i) a 5.5-year triple-A-rated zero coupon note plus (ii) a 5.5-year European call option, or warrant, on the S&P 500 with a strike price of 336.69.

Although both abstracts address similar topics, they are presented in dramatically different ways. Abstract (2), written by the male author, is striking for its heavy utilization of cardinal numbers (e.g., “$100 million”, “5.5 years”, “above 336.69”), which are mostly avoided by the female author. Abstract (1), by contrast, stands out for its greater utilization of “connector words” (e.g., “and”) and questions, the latter of which are not used at all in Abstract (2). The female abstract reads a lot like a story, building a relationship with the reader through the use of pronouns, present tense, asking questions, and by stringing the clauses together with “and” in a loose, storytelling-like manner; the male abstract is focused on relaying the factual information, via the use of numbers and determiners, and past tense. Figure 2 shows the full text of both abstracts, zoomed out, with informational and involved features highlighted in different colors (blue for informational, yellow for involved).

While the gender differences highlighted in the cases above are somewhat unusual in degree, the general pattern is consistent across papers and patents in our larger sample. Figure 3 show the distribution of the Involved-Informational Ratio, stratified by author gender, for paper and patent abstracts, respectively. In both figures, we observe a clear pattern wherein, as the Involved-Informational Ratio increases, so too does the share of female abstracts (as indicated in the figure, the observed gender differences are statistically significant). Note in the patents, the number of bins is smaller because we observe a narrower range of Involved-Informational Ratio values for patents, perhaps reflecting the more constrained style of the genre.
Figure 2. Writing samples. Excerpts from two academic paper abstracts, one written by a female author (1) and the other written by a male (2). Both papers were published in the same field (Business & Economics), in the same journal (Financial Management Journal), during the same time period (1990s). Blue represents informational features, orange represents involved features.

Female

Why do companies in the United Kingdom pay scrip (i.e., in stock) dividends? Are tax savings the sole motive for this option? If so, are all tax-loss companies offering this option? Or is this option driven primarily by nonfinancial considerations? To answer these questions, I conduct a dynamic replication strategy using the Black-Scholes model to account for dividend-paying stocks, was expected to be $2.30. The value of the arbitrage created through the introduction of SIGNS equals the sum of (i) the tax benefit resulting from the investor’s ability to defer income taxes on the amortization of the zero coupon bond component ($0.11 per SIGN) and (ii) the tax benefit resulting from the investor’s ability to defer income taxes on the zero coupon component, valued using the Black-Scholes model, is estimated at $2.30.

Male

The rich variety of securities innovations in recent years continues to intrigue academics and practitioners alike. The array of innovative securities includes a wealth of equity-linked debt securities. On January 28, 1991, the Republic of Austria publicly offered $100 million principal amount of a new equity-linked debt security in the United States. The SIGNS were scheduled to mature in approximately 5.5 years. They would make no payments of interest prior to maturity. If the value of the S&P 500 is below 336.68 on the maturity date, the holder will receive $0.14 per SIGN. Conversely, if the value exceeds 336.68, the holder will get $10 plus $0.14 multiplied by the percentage appreciation in the S&P 500 above 336.68. SIGNS may thus be characterized as a package consisting of (i) a 5.5-year triple-A-rated zero coupon note plus (ii) a 5.5-year European call option. As of the Offering Date, the S&P 500 was at a price of 336.68.

The value of each SIGN can be expressed as the sum of (i) the value of the zero coupon bond component plus (ii) the value of the call option component plus (iii) the value resulting from interest on the SIGNS not being taxable until the maturity date plus (iv) the reduction, if any, in transaction costs vis-a-vis acquiring a comparable zero coupon bond and purchasing call options on the S&P 500 separately plus (v) the value, if any, attributable to creating an investment alternative that is not otherwise available to investors who purchased the SIGNS.

On January 28, 1991, the Republic of Austria had outstanding an issue of zero coupon bonds maturing July 17, 1996, that was yielding 8.05% per annum semiannually compounded. Based on this yield curve, the value of the zero coupon component, valued using the Black-Scholes model, was estimated at $2.30.

The value of the tax arbitrage created through the introduction of SIGNS equals the sum of (i) the tax benefit resulting from the investor’s ability to defer income taxes on the amortization of the zero coupon bond component ($0.11 per SIGN) and (ii) the tax benefit resulting from the investor’s ability to defer income taxes on the zero coupon component, valued using the Black-Scholes model, is estimated at $2.30.

The value of the arbitrage created through the introduction of SIGNS equals the sum of (i) the tax benefit resulting from the investor’s ability to defer income taxes on the amortization of the zero coupon bond component ($0.11 per SIGN) and (ii) the tax benefit resulting from the investor’s ability to defer income taxes on the zero coupon component, valued using the Black-Scholes model, is estimated at $2.30.

The value of each SIGN can be expressed as the sum of (i) the value of the zero coupon bond component plus (ii) the value of the call option component plus (iii) the value resulting from interest on the SIGNS not being taxable until the maturity date plus (iv) the reduction, if any, in transaction costs vis-a-vis acquiring a comparable zero coupon bond and purchasing call options on the S&P 500 separately plus (v) the value, if any, attributable to creating an investment alternative that is not otherwise available to investors who purchased the SIGNS.

The value of the arbitrage created through the introduction of SIGNS equals the sum of (i) the tax benefit resulting from the investor’s ability to defer income taxes on the amortization of the zero coupon bond component ($0.11 per SIGN) and (ii) the tax benefit resulting from the investor’s ability to defer income taxes on the zero coupon component, valued using the Black-Scholes model, is estimated at $2.30.

The value of each SIGN can be expressed as the sum of (i) the value of the zero coupon bond component plus (ii) the value of the call option component plus (iii) the value resulting from interest on the SIGNS not being taxable until the maturity date plus (iv) the reduction, if any, in transaction costs vis-a-vis acquiring a comparable zero coupon bond and purchasing call options on the S&P 500 separately plus (v) the value, if any, attributable to creating an investment alternative that is not otherwise available to investors who purchased the SIGNS.

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Figure 3. Distribution of academic paper and patent abstracts by gender and by Involved-Informational Ratio. Number of academic papers/patents by Involved-Informational Ratio bins by gender, as percentage of total.
2.3 Writing Analysis

Table 1 shows the breakdown of informational and involved features for academic papers and patents, respectively. The results there suggest that, in absolute terms, informational features are used significantly more often in both text sources, by both men and women. This distribution seems plausible given the nature of our corpus (i.e., scientific articles and patents are generally concerned with communicating information), and is also consistent with prior work; Biber (1988), for example, situated academic prose closer to the informational dimension, and Argamon et al. (2013) noted the “greater quantification inherent to most non-fiction genres.” Table 2 also shows the mean and standard deviation of involved and informational features combined and the Involved-Informational Ratio in the academic papers and patents samples.

The results of our regression analysis are shown in Tables 3 (papers) and 4 (patents). Beginning with papers, we find, as expected, a statistically significant association between author gender and the Involved-Informational Ratio of paper abstracts ($\beta = 0.02; p < 0.001$, Model 2); relative to men, women tend to use a higher ratio of involved to informational features in their scientific writing. Holding all other variables at their means, the predicted Involved-Informational Ratio (based on Model 2 of Table 3) is about 6.7% greater for female than male authors. Models 4 and 6, also of Table 3, help to unpack this finding by estimating separate regressions predicting the utilization of involved and informational features, respectively. We find that relative to men, women use involved features at a significantly greater rate ($\beta = 0.23; p < 0.001$, Model 4), and informational features at a significantly lower rate ($\beta = -0.18; p < 0.001$, Model 6) in their writing. This suggests that the differences we detect between men and women in the Involved-Informational Ratio is likely driven by both the numerator and the denominator.

While the patterns we observe appear to hold universally across fields of science and technology, we find heterogeneity in the magnitude of the effect. Figure S9 in the Supplementary Materials shows the predicted gender differences by field. The differences are greater in the Social Sciences and Arts & Humanities and less pronounced in Physical Sciences and Technology, which may be explained by the fact that the former fields generally permit greater freedom of stylistic expression and higher use of involved features than the latter fields, which have more restricted stylistic rules (Argamon et al., 2003). Full regression results for each field are presented in Table S8 (for academic papers) and in Table S9 (for patents) in the Supplementary Materials.

Turning next to patents, we find similar patterns. There is a statistically significant association between inventor gender and the Involved-Informational Ratio of patent abstracts ($\beta = 0.00; p < 0.01$, Model 2); relative to men, women tend to use a higher ratio of involved to informational features in their technical writing. Once again holding all other variables at their means, the predicted Involved-Informational Ratio (based on Model 2 of Table 4) is about 2.3% greater for female than male inventors. In Model 2 of Table 4, we evaluate the relationship between the gender of the patent lawyer and the Involved-Informational Ratio of the patent. Here, we find results that are similar to those we observed for inventor gender, with a statistically significant association between lawyer gender and Involved-Informational Ratio ($\beta = 0.01, p < 0.01$, Model 2). The magnitude of the association, however, is larger than what we observed for inventor gender; holding all other variables at their means, the predicted Involved-Informational Ratio (based on Model 2 of Table 4) is about 5.1% greater for patents with female than male attorneys.

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4We evaluated our regression models for multicollinearity; all variance inflation factors were below the conventional threshold of 10, suggesting little multicollinearity among the covariates.
Following our analytical strategy with papers, in Models 4 and 6 (Table 4), we run separate regressions predicting the rate of utilization for informational and involved features, respectively. Here, the findings are a bit more complex. We find that women use both informational ($\beta < 0.14, p < 0.001$, Model 4) and involved ($\beta = 0.41, p < 0.001$, Model 6) features at a significantly greater rate in their writing than men, suggesting that the association we observe between gender and the Involved-Informational Ratio (Model 2) is driven by the numerator. Female lawyers use involved features in their writing at a rate that is statistically indistinguishable from men (Model 4), but statistically fewer informational ones ($\beta = -0.62, p < 0.001$, Model 6).

**Table 1. Informational and involved feature breakdown in academic papers and patents.**
The data represents the academic paper and patent samples used in the analysis.

|               | Academic papers | Patents |
|---------------|-----------------|---------|
|               | Numbers         |         |
|               | Determiners     |         |
|               | Past tense      |         |
| Informational features | mean | STD | p-value | mean | STD | p-value | mean | STD | p-value |
| Female        | 1.52 | 1.80 | <0.01   | 9.93 | 3.07 | <0.01   | 4.50 | 2.46 | <0.01   |
| male          | 1.54 | 1.83 |         | 10.14 | 3.08 |         | 4.45 | 2.40 |         |
| Involved features |     |     |         |     |     |         |     |     |         |
|               | Questions       | “and”   | Pronoun |
|               | mean | STD | p-value | mean | STD | p-value | mean | STD | p-value |
| Female        | 0.03 | 0.19 | 0.13   | 3.16 | 1.49 | <0.01   | 1.60 | 1.53 | <0.01   |
| male          | 0.03 | 0.19 |         | 2.94 | 1.47 |         | 1.58 | 1.51 |         |
| Informational features |     |     |         |     |     |         |     |     |         |
| Numbers       | mean | STD | p-value | mean | STD | p-value | mean | STD | p-value |
| Female        | 1.30 | 2.23 | 0.77   | 15.91 | 3.71 | <0.01   | 4.39 | 2.09 | <0.01   |
| male          | 1.29 | 2.15 |         | 15.44 | 3.76 |         | 4.47 | 2.13 |         |
| Involved features |     |     |         |     |     |         |     |     |         |
| Questions     | mean | STD | p-value | mean | STD | p-value | mean | STD | p-value |
| Female        | NA   | NA   | NA     | 2.75 | 1.50 | <0.01   | 0.33 | 0.62 | 0.52   |
| male          | NA   | NA   |         | 2.60 | 1.43 |         | 0.34 | 0.60 |         |
Table 2. Distribution of involved and informational features in academic papers and patents. This table shows descriptive statistics regarding the presence of involved and informational features combined in the academic paper and patent samples used in the analysis.

|                          | Involved (normalized) | Informational (normalized) | Ratio (normalized) |
|--------------------------|-----------------------|-----------------------------|--------------------|
|                         | mean  | STD  | p-value | mean  | STD  | p-value | mean  | STD  | p-value |
| **Academic papers**      |       |      |         |       |      |         |       |      |         |
| female                   | 4.78  | 2.14 | <0.01   | 15.96 | 4.04 | <0.01   | 0.33  | 0.21 | <0.01   |
| male                     | 4.55  | 2.09 |         | 16.13 | 4.02 |         | 0.31  | 0.20 |         |
| **Patents**              |       |      |         |       |      |         |       |      |         |
| female                   | 3.08  | 1.60 | <0.01   | 21.60 | 4.07 | <0.01   | 0.15  | 0.10 | 0.01    |
| male                     | 2.94  | 1.53 |         | 21.20 | 4.09 |         | 0.15  | 0.13 |         |
Table 3. Involved-Informational Ratio, involved rate, and informational rate for female and male authors. Regression results for predicted outcomes if author is female, with the following dependent variables: Involved-Informational Ratio, involved rate, informational rate. These results represent data across all fields. Detailed regression results by each field are presented in Table S8 in the Supplementary Materials.

| DV: Inv.-Inf. Ratio | DV: Involved rate | DV: Informational rate |
|---------------------|-------------------|------------------------|
| (1)                 | (2)               | (3)                    |
| Author is female (1 = Yes) | 0.02*** | 0.23*** | 0.23*** |
| (0.00)              | (0.01)           | (0.01)                 |
| Constant            | 0.31***          | 4.55***                | 2.70*** |
| (0.00)              | (0.00)           | (0.15)                 |
| Field fixed effects | No               | No                     |
| Year fixed effects  | Yes              | Yes                    |
| N                   | 512520           | 512520                 |
| $r^2$               | 0.0025           | 0.0030                 |

**$p < 0.001$; **$p < 0.01$; *$p < 0.05$**

Table 4. Involved-Informational Ratio, involved rate, and informational rate for female and male inventors. Regression results for predicted outcomes if an inventor or patent lawyer is female, with the following dependent variables: Involved-Informational Ratio, involved rate, informational rate. These results represent data across all patent categories. Detailed regression results by each patent category are presented in Table S9 in the Supplementary Materials.

| DV: Inv.-Inf. Ratio | DV: Involved rate | DV: Informational rate |
|---------------------|-------------------|------------------------|
| (1)                 | (2)               | (3)                    |
| Inventor is female (1 = Yes) | 0.00** | 0.14*** | 0.14*** |
| (0.00)              | (0.02)           | (0.02)                 |
| Lawyer is female (1 = Yes) | 0.02*** | 0.02 | 0.02 |
| (0.00)              | (0.03)           | (0.04)                 |
| Constant            | 0.15***          | 2.94***                | 3.15*** |
| (0.00)              | (0.01)           | (0.01)                 |
| Field fixed effects | No               | No                     |
| Year fixed effects  | Yes              | Yes                    |
| N                   | 32106            | 32106                  |
| $r^2$               | 0.0013           | 0.0021                 |

**$p < 0.001$; **$p < 0.01$; *$p < 0.05$**
2.4 Citation Analysis

Next, we turn to our analysis of gender differences in citations, the results of which are shown in Tables 5 (academic papers) and 6 (patents). We also provide a visualization of our findings in Figure 4. To simplify the presentation, in this section, we only report models predicting citation as a function of the rate of informational and involved feature utilization (i.e., we do not report the results of models that use the Involved-Informational Ratio as a predictor). We found substantially similar results, however, using the ratio measure.

Overall, we observe significant gender homophily in citation patterns. Papers written by female authors receive a greater share of citations from papers with a female first author ($\beta = 4.33, p < 0.001$) and papers with a female last author ($\beta = 3.57; p < 0.001$). The opposite pattern holds for sample papers written by men.

Taking into account the linguistic features, we see a consistent and statistically significant pattern across the outcome measures: papers with higher rates of utilization of involved features in their abstracts tend to be cited at a higher rate by papers with a female first author ($\beta = 0.25, p < 0.001$, Model 1) and papers with a female last author ($\beta = 0.29, p < 0.001$, Model 3). More substantively, we can interpret the coefficient estimates as indicating that for each unit increase in the rate of involved features used, the rate of citation by papers with a female first and last author is predicted to increase by 0.25 and 0.29, respectively. When we consider the use of informational features, however, the pattern flips ($\beta = -0.08, p < 0.001$, Model 1 for citation by papers with a female first author; $\beta = -0.06, p < 0.001$, Model 3 for citation by papers with a female first author). Papers with higher rates of utilization of involved features are cited at a lower rate by papers with a male first author ($\beta = -0.18, p < 0.001$, Model 2) and papers with a male last author ($\beta = -0.30, p < 0.001$, Model 4). We find that the opposite holds for utilization of informational features, although only in models predicting citation by papers with a male first author ($\beta = 0.03, p < 0.01$, Model 2).

Turning to patents, we find results that are generally similar, but much weaker. While patents that use more informational features are less likely to be cited by patents with a female first ($\beta = -0.07, p < 0.001$, Model 1) or last ($\beta = -0.07, p < 0.001$, Model 3) inventor, none of the remaining coefficients tracking the utilization of informational or involved features are statistically significant. These results are not surprising, considering that patent descriptions, as a type of text, allow much less stylistic expression than academic papers do.
**Figure 4. Regression Coefficients for Citation Patterns.** This panel displays plots that illustrate the magnitude and direction of the regression coefficients when the outcome variable is ‘Female first author’, ‘Female second author’, ‘Male first author’, or ‘Male second author’. (A) This plot reveals that papers written by female authors receive a greater share of citations from papers with a female first author and papers with a female last author; the opposite pattern holds for papers written by men. (B) This plot indicates that papers with higher rates of involved features tend to be cited at a higher rate by papers with a female first author and papers with a female last author; whereas papers with higher rates of involved features are cited at a lower rate by papers with a male first author. The involved rate was an insignificant predictor across all models for patents. (C) This plot shows that papers and patents authored by females, as either the first or last author, have a lower rate of informational features. Papers with a male first author were more likely to utilize informational features. But, informational rates are statistically insignificant for patents authored by males both as first and last authors. **Note:** The regression coefficients on the y-axis display a wider range for (A) compared to (B) and (C). The stars above each bar denote levels of significance (*p < 0.05; **p < 0.01; ***p < 0.001), and ‘n.s.’ indicates ‘not significant’.
Table 5. Involved and informational rates for female and male authors by citation patterns. Regression results for predicted outcomes if author is female, with the following dependent variables: rate of citations from papers with a female, male first author and with a female, male last author. These results represent data across all fields.

|                      | (1) DV: Rate of citations from papers with a female first author | (2) DV: Rate of citations from papers with a male first author | (3) DV: Rate of citations from papers with a female last author | (4) DV: Rate of citations from papers with a male last author |
|----------------------|---------------------------------------------------------------|---------------------------------------------------------------|---------------------------------------------------------------|---------------------------------------------------------------|
| Involved rate        | 0.25***                                                       | -0.18***                                                      | 0.29***                                                      | -0.30***                                                      |
|                      | (0.02)                                                        | (0.02)                                                        | (0.02)                                                        | (0.02)                                                        |
| Informational rate   | -0.08***                                                      | 0.03**                                                        | -0.06***                                                      | -0.01                                                         |
|                      | (0.01)                                                        | (0.01)                                                        | (0.01)                                                        | (0.01)                                                        |
| Author is female (1 = Yes) | 4.33***                                                      | -4.33***                                                      | 3.57***                                                      | -3.64***                                                      |
|                      | (0.07)                                                        | (0.08)                                                        | (0.07)                                                        | (0.08)                                                        |
| Paper is cited 0 times (1 = Yes) | -29.11***                                                      | -51.19***                                                      | -25.80***                                                      | -55.35***                                                      |
|                      | (0.08)                                                        | (0.08)                                                        | (0.08)                                                        | (0.08)                                                        |
| Constant             | 27.16***                                                      | 53.38***                                                      | 23.12***                                                      | 59.00***                                                      |
|                      | (0.20)                                                        | (0.22)                                                        | (0.19)                                                        | (0.22)                                                        |
| Field fixed effects  | Yes                                                          | Yes                                                          | Yes                                                          | Yes                                                          |
| Year fixed effects   | Yes                                                          | Yes                                                          | Yes                                                          | Yes                                                          |
| N                    | 512520                                                        | 512520                                                        | 512520                                                        | 512520                                                        |
| r2                   | 0.3084                                                        | 0.4720                                                        | 0.2748                                                        | 0.5244                                                        |

Notes: Robust standard errors are shown in parentheses; p-values correspond to two-tailed tests.
*p<0.1; **p<0.05; ***p<0.01
Table 6. Involved and informational rates for female and male inventors by citation patterns. Regression results for predicted outcomes if inventor or patent lawyer is female, with the following dependent variables: rate of citations from papers with a female, male first author and with a female, male last author. These results represent data across all fields.

|                     | (1) DV: Rate of citations from patents with a female first inventor | (2) DV: Rate of citations from patents with a male first inventor | (3) DV: Rate of citations from patents with a female last inventor | (4) DV: Rate of citations from patents with a male last inventor |
|---------------------|-------------------------------------------------------------|-------------------------------------------------------------|-------------------------------------------------------------|-------------------------------------------------------------|
| Involved rate       | 0.02 (0.05)                                                | 0.20+ (0.11)                                               | 0.04 (0.05)                                                | 0.12 (0.11)                                                |
| Informational rate  | -0.07*** (0.02)                                            | 0.04 (0.04)                                                | -0.07*** (0.02)                                            | 0.04 (0.04)                                                |
| Inventor is female  | 2.78*** (0.16)                                             | -3.09*** (0.34)                                            | 2.75*** (0.16)                                             | -3.20*** (0.34)                                            |
| Lawyer is female    | 0.31 (0.33)                                                | 0.21 (0.69)                                                | 0.03 (0.33)                                                | 0.50 (0.68)                                                |
| Patent is cited 0   | -5.02*** (0.13)                                            | -41.99*** (0.29)                                           | -5.52*** (0.14)                                            | -41.42*** (0.29)                                           |
| Constant            | 5.13*** (0.48)                                             | 42.39*** (1.09)                                            | 5.41*** (0.50)                                             | 42.25*** (1.08)                                            |
| Field fixed effects | Yes                                                       | Yes                                                       | Yes                                                       | Yes                                                       |
| Year fixed effects  | Yes                                                       | Yes                                                       | Yes                                                       | Yes                                                       |
| N                   | 32106                                                     | 32106                                                     | 32106                                                     | 32106                                                     |
| r2                  | 0.0589                                                    | 0.2963                                                    | 0.0575                                                    | 0.2964                                                    |

Notes: Robust standard errors are shown in parentheses; p-values correspond to two-tailed tests.
*p<0.1; **p<0.05; ***p<0.01
3 Discussion

The norm of universalism in science and technology stipulates that the evaluation of scientific and technological contributions should be based on impersonal criteria (Merton and Storer, 1973). Nevertheless, growing evidence suggests that gender gaps in scholarly assessment remain both prevalent and widespread (Moss-Racusin et al., 2012; Reuben et al., 2014; Oliveira et al., 2019; Card et al., 2020a). In this study, we examined variation in writing style by gender in scientific and technical texts, and considered the role this variation plays in the citation patterns. To do so, we developed an approach motivated by a larger linguistic framework, examining differences between “involved” and “informational” writing styles.

Based on our sample of single-authored academic papers and patents, we find differences in the writing styles of female and male authors, with female writers using involved features more frequently in their work (features associated with more affective, interactional content), a pattern that holds across all scientific fields and patent subcategories. These differences are greater in the Social Sciences and Arts & Humanities and less pronounced in Physical Sciences, likely because the former fields allow for more stylistic expression. In the patent data, we find that the gender of the lawyer is more predictive of this pattern, suggesting that lawyers have a greater influence on the editing of the patent description. The same pattern holds in the citation analysis, where papers with higher rates of utilization of involved features in their abstracts tend to be cited at a higher rate by papers with a female first author and papers with a female last author.

Our work is not without limitations. Importantly, our study inferred the gender of authors and inventors based on their names, which offers only a rough proxy. Moreover, our gender assignments were binary, corresponding to sex-based categories (female and male), which oversimplifies the true diversity of gender identities among authors and inventors. We also limited our attention to single-authored papers and patents and patents with a single lawyer. While this approach helps to make the interpretation of our results clearer, more work needs to be done to determine whether and how our findings apply to teams. Further work on analyzing writing styles of mixed-gender teams could help provide a more nuanced understanding of the observed pattern. Finally, our study is based on observational data, and therefore our results should not be interpreted as causal. As such, future behavioral studies, involving experimental assessment of the response of reviewers to highly involved and highly informational texts based on the reviewer’s gender, would complement our corpus study of academic papers and patents.

Notwithstanding these limitations, our study makes several contributions. First, our study adds to the Science of Science. Specifically, we propose an analysis with a set of linguistic features which is motivated by a an involved/informational framework, established in the linguistic research as indicative of differences in male and female communication styles, which allows us to take a systematic view on understanding gender differences in scientific and technical writing.

Second, our study adds new insights to the linguistics literature. Specifically, we use a larger sample of formal written text and utilize a new source of data (patent descriptions) which to our knowledge has not been used for the purposes of the analysis of gender differences in writing before. We also released an open-source Python package to compute the linguistic features used in this paper for future use of researchers, available here: https://pypi.org/project/stylometer.

Finally, our study also has several natural policy implications. In particular, our findings suggest that writing in science and technology is not completely devoid of personal markers and, therefore, could constitute a potential source of bias during the evaluation processes.
However, establishing rigid guidelines for communication styles in science and technology may not be the right solution. Instead, we suggest that in order to mitigate bias in evaluation processes, the diversity among the contributors should be matched by the same diversity among the evaluators. For example, previous researchers noted the need to increase the number of female reviewers (Kolev et al., 2020), as well as to encourage citation diversity (Zurn et al., 2020) and continue raising awareness of language bias in established institutions, structures, and processes, including academia (Clements and Petray, 2021). Such measures could help to uphold the norm of universalism in scientific contributions.

4 Materials and Methods

4.1 Framework

We draw on a previously established linguistic framework, known as “Informational versus Involved Production,” outlined by Biber (1988), which characterizes the co-occurrence of certain linguistic features based on their communicative function. While the linguistics community has developed a number of potentially applicable frameworks, we chose Biber’s because it was created using a diverse set of corpora, including non-fiction, and was intended to capture universal features of English language; therefore, we anticipate that it would likely capture useful variation across a broad range of scientific and technological fields, encompassing potentially diverse norms of composition. We specifically chose the “informational”/“involved” dimension of Biber’s framework, as studies note (Argamon et al., 2003) that men tend to focus more on relaying factual information (“informational”), while women tend to focus on building a relationship with an audience in their communications (“involved”). Based on a corpus of e-mail communication, speech, and blogs, Pennebaker (2011) stipulated that “males categorize their worlds by counting, naming, and organizing the objects they confront” (informational aspect), while women “personalize their topics” (involved aspect).

Biber outlines two factors that influence the choice of individuals to use a specific linguistic mode: the production circumstances of real-time constraints (speech or conversation) versus editing possibilities (academic writing), and the primary purpose of the writer (informational versus involved). With respect to the production circumstances, given the type of corpus that we are exploring in this study (formal written text), we can hold these constant, as both papers and patents are produced in settings where editing is possible and likely (i.e., the authors are under no real-time constraints, unlike the case of a conversation). With respect to the primary purpose of the writer (informational versus involved), Argamon et al. (2003) noted that formal written text is intended for a “broad unseen audience.” Biber et al. (1998) found that letters written by women and addressed to women were more involved and letters written by men and addressed to men were less involved. He also found that, overall, letters written by women are more involved than letters written by men. Even though in formal written text there is no specific addressee, and academic papers and patent descriptions are intended for a “broad unseen audience”, our goal is to understand if we are still able to observe the variation by the gender of the writers.

In addition to Biber’s framework, the specific set of “involved” and “informational” features used in our study was informed by the follow-up work of Pennebaker (2011) and Argamon et al. (2003). We chose three distinctive features for “involved” and “informational” writing modes (Figure 1). Pronouns, questions, and non-phrasal coordination (“and” connector) are highly correlated as linguistic features and are reflective of the “involved” writing style. The use of pronouns indicates interaction between the writer and the reader—the writer assumes
that the reader knows what they are referring to with a pronoun, as the reader is following the writer’s story in a text; pronouns “present things in a relational way” (Argamon et al., 2003, p. 7). We consider questions to be an important involved feature as well, as they point to the presence of a hypothetical addressee in a formal written text, and are therefore a marker of interaction (Biber, 1986; Marckworth and Baker, 1974). Non-phrasal coordination (“and”) is used “to string clauses together in a loose, logically unspecified manner, instead of integrating the information into fewer units” (Biber, 1988, p. 106), and thus is more associated with a narrative type of communication (“involved” aspect). For “informational” writing mode indicators, we use past tense, determiners, and cardinal numbers. We use past tense as an “informational” feature, to indicate a “disconnection” with the audience, absence of interaction in the narrative. The other two “informational” features—determiners and cardinal numbers—are taken from Argamon et al. (2003) who used the Balanced Winnow algorithm to identify features that are strong indicators of either male or female writing. Argamon and colleagues note that, based on their examination of texts, “the use of determiners reflects that male writers are mentioning classes of things, in contrast to female writers, who are personalizing their messages” (Argamon et al., 2003, p. 12). The greater use of cardinal numbers (quantification) is also noted as a strong male indicator in both the work of Pennebaker (2011) and Argamon et al. (2003).

4.2 Corpus

As noted previously, we draw on two different corpora: (1) abstracts of academic papers from Web of Science5 (“WoS data”) and (2) abstracts of patents from PatentsView (“PatentsView data”)6. Both databases have been widely used in prior research in the Science of Science, and provide generally representative of scientific papers and patented inventions, respectively (Funk and Owen-Smith, 2017; Birkle et al., 2020; Jaffe and Trajtenberg, 2002).

For the WoS data, we excluded document types that are not typically meant for the publication of scientific findings (e.g., book reviews, letters, music scores, and bibliographies). We further limited our attention to articles that included full-text abstracts, and that were written in English7. For the PatentsView data, we limited our attention to utility patents, which encompass roughly 90% of the patents granted by the United States Patent and Trademark Office (USPTO), and have therefore been the central focus of prior work (Jaffe and Trajtenberg, 2002). All patents granted by the USPTO are written in English, and more than 90% (going back to 1976) include full-text abstracts.

For the purposes of our study, we further narrow our focus to solo-authored papers and patents (i.e., we exclude papers and patents written by teams). Our motivation for doing so was to allow for a clearer identification of the relationship between gender and writing style, which would be more complex in the case of teams, particularly those of mixed gender. Note that in the patent data, we also narrowed our sample to include only those inventors with a single lawyer, in order to more cleanly control for gender. In addition, we require that abstracts have more than 100 words, in order to normalize frequency counts per 100 words, which is consistent with prior research in linguistics (Biber, 1988). Additional details on the procedure used to narrow down our samples from the population of articles and patents, including the number of observations lost at each stage, are given in Figure S6 in the Supplementary Materials.

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5Web of Science: https://clarivate.com/webofsciencegroup/solutions/web-of-science/

6PatentsView: http://www.patentsview.org/

7The WoS data do not include accurate information on the language of paper abstracts. We identified English language abstracts using a commercial machine translation API.
Women are underrepresented in the population of both authors and inventors. For perspective, in our data, roughly 19.6% of authors and 5.4% of inventors are women. Moreover, men and women tend to publish in different areas, and their relative representation changes over time. Therefore, to help facilitate comparisons, we subset the WoS and PatentsView data by building a matched sample of papers and patents written by male and female authors and inventors. To do so, we identified, for each academic paper written by a single female author in a particular WoS subject area (e.g., “Sociology”, “Cell Biology”, “Mathematics”) and in a particular year, a corresponding academic paper written by a single male author in the same subject area and year. We follow a similar procedure for patents, using National Bureau of Economic Research (NBER) patent subcategories to proxy for the field of technology, and the grant year of the patent as the year of publication.

For the WoS data, we subset the corpus to years starting in 1991, as abstracts are not well represented in earlier periods (Figure 5). After matching, most of the abstracts in our final analytical sample are from the Social Sciences, followed by Life Sciences and Biomedicine. (Figure S7 in the Supplementary Materials shows the distribution of fields in the original Web of Science corpus.) This is consistent with prior work, as women are well represented in the social sciences and biomedical domains (Ceci et al., 2014; Su and Rounds, 2015). For the PatentsView data, our analysis begins in 1976, which is the first year in which machine readable patent records are available from the USPTO. After matching, most patents come from the “Others” NBER category, which includes “Miscellaneous” patent types. (Figure S8 in the Supplementary Materials shows the distribution of categories in the original PatentsView corpus.)

Gender is assigned using author and inventor names. For papers, author gender is coded based on first and (when available) middle names, as reported in the Web of Science database, using the genderize.io application programming interface (API). For patents, we assign inventor gender by using a coding provided by the United States Patent and Trademark Office, as included with the PatentsView data. More details about the gender assignment can be found in the Supplementary Text section of Supplementary Materials.

### 4.3 Linguistic Measures

For each paper and patent in our sample, we constructed a series of measures tracking the utilization of informational and involved features. We use pronouns, questions, and non-phrasal coordination (“and” connector) as indicators of the “involved” style of writing, and past tense, determiners, and cardinal numbers as indicators of “informational” style of writing. Figure 1 gives an overview of the specific features of interest; more details about the computation of these features are included in the Table S7 in the Supplementary Materials.⁹

We define three separate measures: involved rate, informational rate, and Involved-Informational Ratio. Because our corpus includes academic writing and invention descriptions, there is already a high utilization of informational features by both female and male authors; therefore, in addition to involved and informational rates, we are also interested in seeing the relative rate at which writers use involved features in relation to informational features (Involved-Informational Ratio). We define the involved and informational rates as the sum of three involved (or informational) linguistic features divided by the total number of tokens in a given ab-

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⁸This is an estimate for academic papers with one author and for patents with one inventor, where the gender of the author/inventor was known/assigned.

⁹We also released an open-source Python package to compute these linguistic features, available here: https://pypi.org/project/stylometer.
stract, and normalized to units of 100 words (Biber, 1988). We define the Involved-Informational Ratio as the involved rate divided by the informational rate.

\[
\text{Involved Rate} = \frac{N_{\text{pron}} + N_{\text{and}} + N_d}{N_{\text{tokens}}} \times 100
\]  

\[
\text{Informational Rate} = \frac{N_{\text{det}} + N_{\text{past}} + N_{\text{num}}}{N_{\text{tokens}}} \times 100
\]  

\[
\text{Inv.-Inf. Rate} = \frac{\text{Involved Rate}}{\text{Informational Rate}}
\]

To better understand the relationship between author gender and writing style, we estimated a series of linear regression models, predicting the utilization of informational and involved features in paper and patent abstracts. For models of both papers and patents, predictor variables included the gender of the author (or inventor), the year of academic paper (or patent grant), and the principal scientific (or technological) field. For models of patents, we also included as a predictor the gender of the lawyer, as patent attorneys often take part in writing and editing the patent text.

**Figure 5. Distribution of papers and patents by year and by field.** These panels represent data used in the analytical sample. Figure S7 in the Supplementary Materials shows the distribution of categories in the original Web of Science corpus, and Figure S8 in the Supplementary Materials shows the distribution of categories in the original PatentsView corpus.
4.4 Citation measures

The possibility that men and women write in systematically different ways naturally raises questions about the relationship between writing styles and the reception of intellectual products. Specifically, differences in how men and women present their research in written text may help account for some of the disparities in rates of citation documented in prior work (Caplar et al., 2017; Potthoff and Zimmermann, 2017; Dion et al., 2018; Dworkin et al., 2020; Zurn et al., 2020).

To evaluate this possibility, we conducted a series of analyses in which we decomposed the number of citations made by future papers and patents to those in our sample, according to the gender of the citing author or inventor. We emphasize that citation is merely a proxy for (unobservable) reading preferences—authors may cite prior work without reading it; scientists and inventors probably only cite a fraction of the prior work that they do read; and citation need not correspond to a favorable reading of the cited work. Keeping those caveats in mind, for each sample paper and patent, we computed two related measures: (1) citations from papers with a female (male) first author, (2) citations from papers with a female (male) last author. For each measure, we excluded self-citations, i.e., those made by the author of the sample paper to his or her own work. In addition, to facilitate interpretation, we transform each measure into a rate per 100 citations. Subsequently, we estimated a series of regression models, wherein the three measures are our outcomes of interest, and the predictors are the gender of the author or inventor (and lawyer for patents) and the ratio of informational and involved features. For papers and patents cited 0 times, we impute a rate of 0, and add an imputation indicator as a covariate. As with our prior regression, we control for the field and year of academic paper/patent.

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7 Competing interests

The authors declare that they have no competing interests.

8 Data and materials availability

The Python 3, MySQL 8, RStudio1.2, and Stata 16 code used to analyze and visualize the data for the current study will be available from the corresponding author. PatentsView data used in the study are publicly available directly from the publisher. Data from the Web of Science are available from Clarivate Analytics, but restrictions apply to the availability of these data, which were used under license for the current study, and so are not publicly available. These data are however still available from the authors upon reasonable request and with permission from the publisher.
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Supplementary Materials

Gender coding

In this appendix, we describe our procedure for coding the gender of paper authors and patent inventors and lawyers. For papers, we coded author gender based on author first and (when available) middle names, as reported in Web of Science, using the genderize.io application programming interface (API). While similar approaches have been widely used in prior work, we recognize that author names offer only an imperfect proxy for gender, and this limitation should be kept in mind when interpreting the results of our study. Given a name, the genderize.io API returns the most likely gender and an associated probability score. The genderize.io API makes gender suggestions based on worldwide data from hundreds of millions of social media profiles; as such, the service makes a significant improvement over prior approaches, which are typically based on records from the United States Social Security Administration or similar government entities, and that therefore perform poorly on international samples. For our study, we used a probability cutoff of 0.9 for assigning gender; gender suggestions below that level were set to “unknown” and excluded from the study. When possible, we assigned gender by looking across the academic papers of an author. For example, if the same author had published one paper under the name “J. Smith” and the other under the name “John Smith”, we would assign the gender of the author as “male” in both cases, using the name from the latter paper to propagate a gender to the second.

For patents, we assign inventor gender by using the coding provided by the United States Patent and Trademark Office, via its Patents View database. Similar to our approach for papers, the Patents View database assigns gender based on inventor names. Details on the algorithm are given in (Toole et al., 2021). Patents View does not assign gender to patent attorneys. Therefore, we assigned gender ourselves, using an approach analogous to the one described above for papers.
Fig. S6. Identification of the analytical sample

Full Size Dataset

| Publications | Patents |
|--------------|---------|
| 34,210,804   | 3,840,570 |

Only Single Male/Female Author

| Publications* | Patents |
|---------------|---------|
| Single Author, Male | 1,714,804 | 1,964,816 |
| Single Author, Female | 474,839   | 122,772   |

Abstracts with > 100 words

| Publications | Patents |
|--------------|---------|
| Single Author, Male (> 100 words) | 994,589 | 1,334,190 |
| Single Author, Female (> 100 words) | 274,804 | 79,720   |

| Patents |
|---------|
| Single Author, Male (> 100 words) + Single Lawyer | 1,232,002 |
| Single Author, Female (> 100 words) + Single Lawyer | 70,858   |

Matching by subject/subcategory and by year

| Publications | Patents |
|--------------|---------|
| Single Author, Male (> 100 words) + Matched by subject and year | 256,260 |
| Single Author, Female (> 100 words) + Matched by subject and year | 256,260 |

| Patents |
|---------|
| Single Author, Male (> 100 words) + Single Lawyer + Matched by subcategory and year | 16,053 |
| Single Author, Female (> 100 words) + Single Lawyer + Matched by subcategory and year | 16,053 |
Fig. S7. Distribution of papers included in the full WoS data by field

Source: Web of Science
Fig. S8. Distribution of patents included in the full PatentsView data by category

Source: PatentsView
Fig. S9. Gender differences by field in academic papers. The regression coefficients (predicted gender differences) are derived from Table 3. The x-axis represents Web of Science subject categories (fields).
Table S7. Linguistic feature construction

Linguistic features are computed using spaCy library in Python (Honnibal and Montani, 2017). Tags in spaCy are based on OntoNotes 5 version of the Penn Treebank tag set (Weischedel et al., 2013).

| Tag | Source | Description | Feature | Dimension |
|-----|--------|-------------|---------|-----------|
| CD  | spaCy  | Cardinal number | Number | Informational |
| PDT | spaCy  | Predeterminer (e.g. both, etc.) | Determiner | Informational |
| WDT | spaCy  | Wh-determiner (e.g. which, etc.) | Determiner | Informational |
| DT  | spaCy  | Determiner | Determiner | Informational |
| VBD | spaCy  | Verb, past tense | Past tense | Informational |
| VBN | spaCy  | Verb, past participle | Past tense | Informational |
| PRP | spaCy  | Personal pronoun | Pronoun | Involved |
| PRPS| spaCy  | Possessive pronoun | Pronoun | Involved |
| WP  | spaCy  | Wh-pronoun | Pronoun | Involved |
| WPS | spaCy  | Possessive wh-pronoun | Pronoun | Involved |
| AND | string match | Connector “and” | Connector | Involved |
| ?   | string match | Question mark | Question | Involved |
Table S8. Gender differences in writing style by field for academic papers (full regression results). Regression models in this table replicate those of Table 3, but separately by WoS research area. **p < 0.001; *p < 0.01; *p < 0.05

| Physical Sciences | DV: Inv.-Inf. Ratio | DV: Involved rate | DV: Informational rate |
|-------------------|---------------------|-------------------|-----------------------|
|                    | (1)                 | (2)               | (3)                   | (4)                    | (5)                       | (6)                       |
| Author is female (1 = Yes) | 0.0049*** (0.0012) | 0.0046*** (0.0011) | 0.1170*** (0.0136) | 0.1136*** (0.0134) | 0.2085*** (0.0311) | 0.2145*** (0.0303) |
| Constant           | 0.2314*** (0.0008)  | 0.1668** (0.0540)  | 3.6371*** (0.0096)  | 3.2202*** (0.6325) | 17.1514*** (0.0220) | 19.0286*** (1.4339) |
| N                 | 62358               | 62358             | 62358                | 62358                 | 62358                   | 62358                    |
| r²                | 0.0003              | 0.0544            | 0.0012               | 0.0484               | 0.0007                  | 0.0576                   |

| Technology        | DV: Inv.-Inf. Ratio | DV: Involved rate | DV: Informational rate |
|-------------------|---------------------|-------------------|-----------------------|
|                    | (1)                 | (2)               | (3)                   | (4)                    | (5)                       | (6)                       |
| Author is female (1 = Yes) | 0.0096*** (0.0016) | 0.0101*** (0.0015) | 0.1404*** (0.0179) | 0.1444*** (0.0169) | 0.0162                   | 0.0018                   |
| Constant           | 0.2491*** (0.0011)  | 0.1602** (0.0134)  | 3.8901*** (0.0127)  | 2.8286*** (0.1478) | 17.3202*** (0.0272) | 19.2278*** (0.3239) |
| N                 | 43675               | 43675             | 43675                | 43675                 | 43675                   | 43675                    |
| r²                | 0.0008              | 0.1160            | 0.0014               | 0.1176               | 0.0000                  | 0.0811                   |

| Life Sciences & Biomedicine | DV: Inv.-Inf. Ratio | DV: Involved rate | DV: Informational rate |
|----------------------------|---------------------|-------------------|-----------------------|
|                            | (1)                 | (2)               | (3)                   | (4)                    | (5)                       | (6)                       |
| Author is female (1 = Yes) | 0.0185*** (0.0010)  | 0.0186*** (0.0010) | 0.2046*** (0.0096)  | 0.2053*** (0.0090) | −0.1583***                | −0.1571***                |
| Constant                   | 0.2893*** (0.0007)  | 0.1160*** (0.0134) | 4.1138*** (0.0068)  | 2.2907*** (0.1259) | 15.9629***                | 19.3331***                |
| N                           | 149541              | 149541            | 149541               | 149541                | 149541                   | 149541                   |
| r²                          | 0.0023              | 0.1007            | 0.0030               | 0.1230                | 0.0003                  | 0.0892                   |

| Arts & Humanities          | DV: Inv.-Inf. Ratio | DV: Involved rate | DV: Informational rate |
|----------------------------|---------------------|-------------------|-----------------------|
|                            | (1)                 | (2)               | (3)                   | (4)                    | (5)                       | (6)                       |
| Author is female (1 = Yes) | 0.0275*** (0.0018)  | 0.0276*** (0.0017) | 0.2787*** (0.0177)  | 0.2779*** (0.0176) | −0.3846***                | −0.3874***                |
| Constant                   | 0.3860*** (0.0013)  | 0.3551*** (0.0835) | 5.7840*** (0.0125)  | 4.3604*** (0.8482) | 16.4391***                | 14.6273***                |
| N                           | 64317               | 64317             | 64317                | 64317                 | 64317                   | 64317                    |
| r²                          | 0.0037              | 0.0556            | 0.0038               | 0.0232                | 0.0025                  | 0.1148                   |

| Social Sciences            | DV: Inv.-Inf. Ratio | DV: Involved rate | DV: Informational rate |
|----------------------------|---------------------|-------------------|-----------------------|
|                            | (1)                 | (2)               | (3)                   | (4)                    | (5)                       | (6)                       |
| Author is female (1 = Yes) | 0.0283*** (0.0010)  | 0.0282*** (0.0010) | 0.2959*** (0.0097)  | 0.2949*** (0.0095) | −0.2911***                | −0.2899***                |
| Constant                   | 0.3482*** (0.0007)  | 0.2189*** (0.0530) | 4.9205*** (0.0069)  | 3.2420*** (0.5159) | 15.5635***                | 16.0783***                |
| N                           | 192629              | 192629            | 192629               | 192629                | 192629                   | 192629                   |
| r²                          | 0.0042              | 0.0453            | 0.0048               | 0.0587                | 0.0015                  | 0.0499                   |
Table S9. Gender differences in writing style by field for patents (full regression results).
Regression models in this table replicate those of Table 4, but separately by NBER category. 

**p < 0.001; **p < 0.01; *p < 0.05

| Field            | DV: Inv.-Inf. Ratio | DV: Involved rate | DV: Informational rate |
|------------------|---------------------|-------------------|------------------------|
|                   | (1)                 | (2)               | (3)                    | (4)                    | (5)                    | (6)                    |
|                   | Constant            |                   |                        |                        |                        |                        |
|                   | 0.0044              | 0.0004            | 0.0578                  | 0.0578                | 0.3038**             | 0.3034**               |
|                   | (0.0026)            | (0.0026)          | (0.0412)               | (0.0411)              | (0.1064)             | (0.1054)               |
|                   | Lawyer is female (1 = Yes) |                   |                        |                        |                        |                        |
|                   | 0.0102*             | 0.0093            | 0.0373                  | 0.0356                | −0.7366***           | −0.6249***             |
|                   | (0.0051)            | (0.0051)          | (0.0799)               | (0.0802)              | (0.2065)             | (0.2057)               |
|                   | Constant            |                   |                        |                        |                        |                        |
|                   | 0.1363***           | 0.1314***         | 2.6626***               | 2.6891***             | 20.9118***           | 20.9487***             |
|                   | (0.0019)            | (0.0178)          | (0.0296)               | (0.2812)              | (0.0766)             | (0.7211)               |
| Field fixed effects | No                  | No                |                        |                        |                        |                        |
| Year fixed effects | Yes                 | Yes               |                        |                        |                        |                        |
|                   | N                   | 5580              | 5580                    | 5580                   | 5580                   | 5580                   |
|                   | r²                  | 0.0007            | 0.0156                  | 0.0004                 | 0.0121                | 0.0037                 | 0.0311                 |

| Field            | DV: Inv.-Inf. Ratio | DV: Involved rate | DV: Informational rate |
|------------------|---------------------|-------------------|------------------------|
|                   | (1)                 | (2)               | (3)                    | (4)                    | (5)                    | (6)                    |
|                   | Constant            |                   |                        |                        |                        |                        |
|                   | 0.0076**            | 0.0076**          | 0.2715***               | 0.2716***              | 0.8669***             | 0.8668***              |
|                   | (0.0026)            | (0.0026)          | (0.0436)               | (0.0435)              | (0.1176)             | (0.1156)               |
|                   | Lawyer is female (1 = Yes) |                   |                        |                        |                        |                        |
|                   | 0.0053              | 0.0048            | 0.0183                  | 0.0034                | −0.6147*              | −0.5997*               |
|                   | (0.0054)            | (0.0054)          | (0.0910)               | (0.0914)              | (0.2455)             | (0.2431)               |
|                   | Constant            |                   |                        |                        |                        |                        |
|                   | 0.1340***           | 0.1366***         | 2.7003***               | 2.9902***             | 21.2449***           | 22.2313***             |
|                   | (0.0018)            | (0.0120)          | (0.0312)               | (0.2046)              | (0.0843)             | (0.5441)               |
| Field fixed effects | No                  | No                |                        |                        |                        |                        |
| Year fixed effects | Yes                 | Yes               |                        |                        |                        |                        |
|                   | N                   | 4632              | 4632                    | 4632                   | 4632                   | 4632                   |
|                   | r²                  | 0.0021            | 0.0186                  | 0.0083                 | 0.0235                | 0.0128                 | 0.0558                 |

| Field            | DV: Inv.-Inf. Ratio | DV: Involved rate | DV: Informational rate |
|------------------|---------------------|-------------------|------------------------|
|                   | (1)                 | (2)               | (3)                    | (4)                    | (5)                    | (6)                    |
|                   | Constant            |                   |                        |                        |                        |                        |
|                   | −0.0012             | −0.0012           | 0.1130*                 | 0.1129*                | 0.9326***             | 0.9319***              |
|                   | (0.0025)            | (0.0025)          | (0.0456)               | (0.0454)              | (0.1149)             | (0.1133)               |
|                   | Lawyer is female (1 = Yes) |                   |                        |                        |                        |                        |
|                   | 0.0104              | 0.0100            | 0.0477                  | 0.0711                | −1.1050***           | −0.8692***             |
|                   | (0.0057)            | (0.0057)          | (0.1033)               | (0.1042)              | (0.2603)             | (0.2601)               |
|                   | Constant            |                   |                        |                        |                        |                        |
|                   | 0.1445***           | 0.1516***         | 2.9765***               | 3.2065***             | 21.5424***           | 22.2318***             |
|                   | (0.0018)            | (0.0100)          | (0.0326)               | (0.1816)              | (0.0822)             | (0.4531)               |
| Field fixed effects | No                  | No                |                        |                        |                        |                        |
| Year fixed effects | Yes                 | Yes               |                        |                        |                        |                        |
|                   | N                   | 4536              | 4536                    | 4536                   | 4536                   | 4536                   |
|                   | r²                  | 0.0008            | 0.0129                  | 0.0014                 | 0.0195                | 0.0180                 | 0.0552                 |

| Field            | DV: Inv.-Inf. Ratio | DV: Involved rate | DV: Informational rate |
|------------------|---------------------|-------------------|------------------------|
|                   | (1)                 | (2)               | (3)                    | (4)                    | (5)                    | (6)                    |
|                   | Constant            |                   |                        |                        |                        |                        |
|                   | 0.0034              | 0.0040            | 0.1690**                | 0.1702**               | 0.0993                | 0.0615                 |
|                   | (0.0069)            | (0.0068)          | (0.0588)               | (0.0583)              | (0.1651)             | (0.1464)               |
|                   | Lawyer is female (1 = Yes) |                   |                        |                        |                        |                        |
|                   | 0.0333**            | 0.0047            | 0.1021                  | 0.0420                | −2.0064***           | −0.2036                |
|                   | (0.0112)            | (0.0117)          | (0.0950)               | (0.0995)              | (0.2667)             | (0.2495)               |
|                   | Constant            |                   |                        |                        |                        |                        |
|                   | 0.1689***           | 0.2024**          | 3.0063**                | 3.2853**              | 20.3865***           | 18.1602***             |
|                   | (0.0050)            | (0.0775)          | (0.0426)               | (0.6605)              | (0.1195)             | (1.6570)               |
| Field fixed effects | No                  | No                |                        |                        |                        |                        |
| Year fixed effects | Yes                 | Yes               |                        |                        |                        |                        |
|                   | N                   | 3056              | 3056                    | 3056                   | 3056                   | 3056                   |
|                   | r²                  | 0.0030            | 0.0405                  | 0.0031                 | 0.0332                | 0.0182                 | 0.2395                 |
Table S3 (continued). Gender differences in writing style by field for patents (full regression results). Regression models in this table replicate those of Table 4, but separately by NBER category. \( **p < 0.001; *p < 0.01; *p < 0.05 \)

| Chemical | DV: Inv.-Inf. Ratio (1) | DV: Involved rate (3) | DV: Informational rate (6) |
|----------|-------------------------|-----------------------|---------------------------|
| Inventor is female (1 = Yes) | -0.0004 (0.0070) | -0.0004 (0.0069) | 0.0743 (0.0607) | 0.0739 (0.0607) | -0.0344 (0.1777) | -0.0371 (0.1660) |
| Lawyer is female (1 = Yes) | 0.0125 (0.0118) | 0.0101 (0.0118) | -0.0121 (0.1017) | 0.0143 (0.1036) | -1.4362*** (0.2974) | -1.2652*** (0.2831) |
| Constant | 0.1725*** (0.0051) | 0.2024*** (0.0379) | 3.0471*** (0.0439) | 2.8248*** (0.3318) | 19.8252*** (0.1285) | 16.3100*** (0.9070) |

| Others | DV: Inv.-Inf. Ratio (1) | DV: Involved rate (3) | DV: Informational rate (6) |
|--------|-------------------------|-----------------------|---------------------------|
| Inventor is female (1 = Yes) | 0.0056*** (0.0017) | 0.0056*** (0.0017) | 0.1542*** (0.0293) | 0.1537*** (0.0293) | 0.2651*** (0.0699) | 0.2603*** (0.0691) |
| Lawyer is female (1 = Yes) | 0.0084* (0.0036) | 0.0079* (0.0037) | -0.0074 (0.0623) | 0.0198 (0.0630) | -0.7232** (0.1487) | -0.4835*** (0.1487) |
| Constant | 0.1495*** (0.0012) | 0.1559*** (0.0085) | 3.1071*** (0.0209) | 3.1456*** (0.1441) | 21.8632*** (0.0499) | 21.8371*** (0.3427) |

| Field fixed effects | Year fixed effects | N | r² |
|---------------------|--------------------|---|----|
| No                  | Yes                | 2524 | 0.0004 |
| Yes                 | No                 | 2524 | 0.0464 |
| No                  | Yes                | 2524 | 0.0006 |
| Yes                 | No                 | 2524 | 0.0185 |
| No                  | Yes                | 2524 | 0.0092 |
| Yes                 | No                 | 2524 | 0.1501 |

| N | 11778 | 11778 | 11778 | 11778 | 11778 | 11778 |
|---|-------|-------|-------|-------|-------|-------|
| r² | 0.0014 | 0.0065 | 0.0024 | 0.0087 | 0.0031 | 0.0312 |