Reading between the Emails: Gendered Patterns of Communication in Local Government

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In this paper, we study the role of gender in local government organizations. We analyze email data from seventeen county governments in North Carolina to understand the relationship between a department manager's gender and the emails they send and receive. First, we use descriptive statistics to identify aggregate gender-homophilous and gender-heterophilous patterns from the numbers of emails sent and received by all department managers. In contrast to previous research, we find no strong evidence of either gender homophily or heterophily. To investigate this finding, we therefore analyze department-to-department communication patterns. Here, we do find evidence of gender bias, with some departments exhibiting gender homophily and others exhibiting heterophily. Finally, to determine the extent to which these patterns are driven by communication content, we use a recently developed latent variable model to identify topic-specific communication subnetworks for each county. Using both approaches, we find robust patterns in terms of how interaction depends upon gender across discussion domains. Our results agree with recent findings in the literature indicating that females are more active in small groups when the groups are majority female.

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Gender in Organizations

Researchers have observed and documented gender bias in both the public and private sectors. Women often receive lower pay, hold less prestigious positions, have reduced opportunities for advancement, and are excluded from decision-making coalitions [5, 3, 14, 2, 9]. As a result, organizations that aspire to a just, efficient, and sustainable culture strive to provide men and women with equal treatment in the workplace [11]. In practice, however, these organizations and the researchers who study them have found it hard to fully understand the day-to-day causes and extent of gender bias. The limited availability of primary-source data means that most research is based on small-scale observational, ethnographic, or self-reported data [e.g., 6, 1, 10]. Since these data sources are often restricted in scope and can be biased by subjective assessments, their use in understanding gender bias is limited.

In this paper, we take a different approach and instead base our analyses on email communication data. We focus specifically on local government organizations and seek to understand the role of gender in communication at the department manager level. With the increasing use of electronic communication in the workplace, and the rise of transparency initiatives within government, scholars can now use public records requests to gather primary-source data about government organizations. Moreover, for many government organizations, such requests even extend to emails. We draw upon this resource to construct an email data set spanning seventeen county governments in North Carolina. By relying on public records requests, our data collection process is replicable. The resultant data set provides a micro-level view of manager-to-manager communication in these county governments, and a unique opportunity to study the relationship between a department manager's gender and the emails they send and receive.

We start by analyzing aggregate communication patterns from the numbers of emails sent and received by all department managers. In contrast to previous research, we find no strong evidence of the kinds of gender-homophilous or gender-heterophilous patterns that suggest gender bias. To unpack this finding, we investigate whether different discussion domains exhibit different communication patterns, using the sender's department as a proxy for discussion domain. By analyzing department-to-department communication patterns, we do find evidence of gender bias, with some departments exhibiting homophily and others exhibiting heterophily. Finally, to determine whether these patterns are driven by communication content rather than other factors correlated with managers' departments, we use a recently developed latent variable model to identify topic-specific communication subnetworks for each county. We find differing degrees of gender homophily and heterophily for different topics of communication.

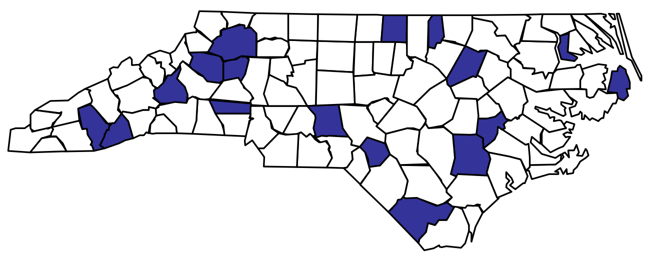


Fig. 1. The seventeen North Carolina counties used in our analysis (shaded).

Table 1. The numbers of male and female department managers for each county, along with the number of manager-to-manager emails sent.

	Manager Gender		
County	Male	Female	# Emails
Alexander	12	9	907
Caldwell	12	8	121
Chowan	12	11	2,027
Columbus	14	10	920
Dare	15	12	2,247
Duplin	13	14	1,914
Hoke	13	11	1,106
Jackson	18	6	1,499
Lenoir	15	5	560
Lincoln	15	7	573
McDowell	12	5	326
Montgomery	8	10	680
Nash	11	8	1,147
Person	12	9	1,491
Transylvania	16	4	1,857
Vance	10	8	185
Wilkes	15	2	303
Total	223	139	17,863

[1]Our validation experiments indicate a 100 percent agreement between human coding of our emails and our automated text extraction approach. A separate technical report detailing these efforts is available upon request.

Data

We selected the state of North Carolina for our study because its public records laws explicitly mention email data and prevent counties from charging unreasonable fees for fulfilling requests. To construct our email data set, we issued public records requests to the one hundred North Carolina county governments. Our request to each county covered all emails sent and received by the department managers (e.g., health, finance, and elections) over a randomly selected period of three months in 2013. Twenty-three counties complied with our request, of which seventeen provided sufficient data for our analyses in an electronic format. Figure 1 indicates the seventeen counties. These counties are statistically indistinguishable from the other eighty-three counties in North Carolina along various demographic dimensions, including population, per-capita income, and percentage of the population that is white. In total, these seventeen counties produced over half a million emails, including 17,863 that were sent by a department manager to at least one other department manager in the same county (as well as other recipients, in some cases). We restricted our analyses to these manager-to-manager emails. To augment this data set, we also gathered information on the department affiliation and gender of each of the 362 managers represented in our data set. We provide some descriptive statistics for each county in table 1. Overall, almost 40% of the department managers are women, though there is significant variation across counties.

We also took a number of steps to prepare the text of these emails for analysis. We began by removing any quoted text using a series of heuristics and indicators provided by the email program which was used to create them (for example microsoft outlook email files share a common delineator for quoted text). We then ran the text of the emails through the Stanford CoreNLP text processing libraries [16] and named entity recognizer [12] to tokenize the text and remove any resulting tokens that were classified as the name of a person, before removing a list of common and domain specific stopwords. We then preformed a series of validation experiments using the raw email data to verify that the final text we extracted accurately reflected the original email text[1]. Descriptive statistics detailing the number of unique words and total number of tokens in each county email corpus (after preprocessing) is provided in table 2.

Table 2. County email corpus descriptive statistics. The number of tokens is the sum of all tokens (after filtering) in all emails.

	# Emails	# Unique Words	# Tokens
Alexander	907	1595	15437
Caldwell	121	94	2870
Chowan	2027	3038	39635
Columbus	920	1326	13763
Dare	2247	2907	38174
Duplin	1914	2380	83162
Hoke	1106	1397	19409
Jackson	1499	2493	34290
Lenoir	560	1340	19780
Lincoln	573	1458	13754
McDowell	326	1178	8863
Montgomery	679	1137	11166
Nash	1147	2214	31629
Person	1491	2618	29153
Transylvania	1857	3157	57431
Vance	185	620	4070
Wilkes	303	510	5594

Table 3. Per-manager email statistics.

	Manager Gender	
	Male	Female
Average # emails sent	48.3	51
Average # recipients per email sent	1.45	1.43
Average # emails received	70.8	71.6

Table 4. Each cell records the number of times a department manager of gender X was included as a recipient of an email sent by a department manager of gender Y. Statistics provided are calculated for all counties combined. Note that each email may have more than one recipient.

		Recipient		
		Male	Female	Total
Sender	Male	9458	6120	15,578
	Female	6,330	3,833	10,163
	Total	15,788	9,953	

Descriptive Analysis

We begin our analysis of the relationship between a department manager's gender and the emails they send and receive, by looking for differences in the propensity for department managers to send emails to other managers of the same gender, and managers of the opposite gender. Table 3 provides some basic descriptive statistics including the average number emails sent and received by male and female department managers in our sample. On average, male and female department managers send and receive a comparable number of emails, and emails sent by male and female department managers have a similar number of recipients. Therefore, if we observe gender differences in email communication, they are unlikely to be driven by some innate difference in the propensity for male and female department managers to send or receive emails.

To test whether the gender of an email sender is related to the gender of its recipients, in aggregate, we construct a contingency table of email sending and receiving by gender (see table 4). We then perform a χ^2 test for independence between the rows and columns. The χ^2 test statistic we obtain indicates that the gender of an email sender and its recipients is not independent ($\chi^2 = 6.4, p = 0.011$). However, inspection of the contingency table indicates that the test statistic is actually driven by mild gender heterophily in communication. Furthermore, the gender differences we observe are substantively quite small, as both male and female department managers send emails to recipients of each gender in rough proportion to their overall representation in the sample (60% to men, 40% to women).

Domain-Dependent Gendered Communication. Within large organizations that perform heterogeneous functions, it is of little value to ask whether communication is gender biased in the aggregate. Broad patterns may be dominated by personal communications or mundane professional interactions that are inconsequential to the direction of the organization or the careers of employees. Examining domain specific pat-

[2] For the rest of the paper, we use the term *gendered* to refer to patterns of communication where we observe statistically significant variation between the propensity for men to send emails to men, men to send emails to women, women to send emails to men, and women to send emails to women.

terns of communication will build upon limited existing findings, which indicate that gendering[2] patterns depend upon the domain or context of communication. For example, Brass [5] finds a higher degree of male-male homophily in communication network content partitions that deal with long range strategic planning. We should also expect female managers to be relatively more likely to send heterophilous ties in communication network content partitions that deal with short and medium term coordination and planning, as research has found that female managers tend to preferentially communicate through formal channels [17] and favor gender-heterophilous instrumental connections [14]. The scope and scale of our data present an unprecedented opportunity for understanding whether and how gendering patterns vary with the domain of communication.

Going forward we use the term "domain" to refer to an organizational function with which a communication instance is concerned (e.g., long-range strategic planning, human resource management, public relations). A single communication instance may be concerned with more than one domain. For example, a discussion thread concerned with composing a job advertisement may involve both the human resource management and public relations domains. Furthermore, individuals may use the same language to discuss different domains. For example, one employee may commend another on the results of a project, exclaiming that the project leader deserves a promotion. Such a communication may concern human resource management, but it may be a show of enthusiasm concerning the domain with which the project is concerned, and have no real bearing on personnel decisions. Given the importance of domain in understanding the structure of organizational communication networks, and the ambiguities that arise in measuring the domain of communication, we take a two-pronged empirical approach to the analysis of domain-dependent communication patterns. Our two empirical analyses are complimentary along two dimensions: (1) the use of within versus across-county variation; and (2) the operationalization of domain through email content versus the department affiliations of the managers.

Department Affiliation as Domain

Governments, and organizations more generally, spawn subordinate partitions in order to separate tasks according to the domain of organizational function. In the current analysis, we use the departmental affiliations of the managers in our data as proxy measures for the domain of organizational function about which managers communicate (or choose not to communicate) with each other. The use of department affiliation to measure communication domain raises a couple of distinct challenges in our strictly within-county e-mail data, which we solve by combining data across counties. First, aside from a few outlying cases, we only observe one or two managers with a given department affiliation in each county (e.g., one parks department manager). This means that we observe very little within-department communication in our data. Second, within each county, we only observe a handful of across-department dyads of a selected type (e.g., one parks/tax departments pair), which means that we cannot identify gendered patterns within counties that are specific to department pairs (i.e., domain-specific).

We solve the problems raised through using department affiliation to proxy domain by looking across counties for comparable department pairs. The department affiliations are comparable across counties, which means that for most department pairings, we observe a mix of male/male, female/female, female/male and male/female dyads. Using the department pairing to divide potential communication ties into domains, by looking across counties, we're able to observe how the intensity of communication within a given domain varies across different gender combinations. Table 5 gives the gender and department affiliation breakdown of managers in our data. Departments were hand coded into one of twenty-five different categories based on the title given in the county directory, to group departments that perform a similar function. Note that not all departments are represented in each county.

In our first approach to domain-specific analysis of gendering, we construct subsets of data that are specific to department pairings, but span all of the counties in which such pairings are observed. Consider, for example, the pairing of "Human Resources" and "Emergency Services" departments (HR and EMS, respectively). There is at least one HR and one EMS manager in fifteen counties. Across all counties we observe eight male/male pairs of HR/EMS managers, twenty-two mixed gender pairs and two female/female pairs. We construct department-pairing-specific datasets such as this for all of the 300 pairings that can be constructed using the twenty-five departments in our data.

For each of the 130 department-pairing datasets in which there is at least one of each gender pairing type, we fit two Poisson models (the base model and the gendered model) to the frequency of communication between managers. Let $y_{ij} \sim \text{Pois}(\exp(\eta_{ij}))$ be the number of e-mails from i to j. In the base model

$$\eta_{ij} = \beta_0,$$

and in the gendered model

$$\eta_{ij} = \beta_1 g_i g_j + \beta_2 g_i(1-g_j) + \beta_3(1-g_i)g_j + \beta_4(1-g_i)(1-g_j),$$

where g_i and g_i are indicators of the genders of the senders and recipients of e-mails, respectively, with males coded 0 and females 1. Since the gendered model reduces to the base model if $\beta_1 = \beta_2 = \ldots = \beta_4$, we use a likelihood-ratio test to evaluate whether the fit of the gendered model, in which separate rates are estimated for each directed gender pairing, is significantly better than the fit of the base (i.e., constant rate) model. We deem a domain, as represented by a pairing of departments, to exhibit gendered communication patterns if the gendered model fits statistically significantly better than the base model, and we use a p value of 0.05 as the threshold for determining statistical significance.

The gendered model fits better in approximately 70% (90 out of 130) of the domains. This result indicates that there is a substantial degree of within-domain gender bias. To summarize domain specific results in those domains in which we find significant gendering, we present lists of domains in which we find a consistent gendering pattern, for the six largest gendering patterns we identify. We take a gendering pattern to be a rank-ordering of the coefficients (β's) in the gendered model. The domains that exhibit the six most prevalent gendering patterns are presented in table 6. The most prevalent gendering pattern, depicted in the first column and first row of Table 6, is characterized by female-centric communication in which both females and males send communications to females at a higher rate than to males, and females send communication at a higher rate than do males. This gendering pattern is dominated by HR departments. The second most prevalent gendering pattern is also female-centric in that senders of both genders communicate more frequently with females than with males. Both the departments of Elections and Emergency Services are disproportionately represented in this pattern, with Elections appearing in pairs only within this pattern of gendering and Emergency Services appearing only once outside

Table 5. Number of male and female managers for each department.

	Emergency	Manager	HR	Finance	IT	Health	Plan/Dev	Util/Waste	Tax	Parks/Rec	Soc_Serv	Transport	Info	Misc	Inspections	Maintenance	Library	Veterans	Seniors	Animal	Elections	Sheriff	Environment	Deeds	Extension
Male	29	15	3	5	11	6	17	15	11	9	8	8	2	5	13	5	3	5	2	9	2	16	9	6	8
Female	3	2	12	12	2	11	6	2	7	5	10	1	6	2	3	1	8	7	6	3	11	1	4	9	5
Total	32	17	15	17	13	17	23	17	18	14	18	9	8	7	16	6	11	12	8	12	13	17	13	15	13

Table 6. Domains in which there is significantly gendered rates of communication grouped by gendering pattern.

FF>FM>MF>MM	FF>MF>FM>MM
HR & Health	Information Technology & Health
HR & Information Technology	HR & Emergency Services
HR & County Manager	Library & County Manager
Planning & HR	Register of Deeds & Information Technology
Register of Deeds & HR	Parks and Recreation & Health
Parks and Recreation & HR	Parks and Recreation & County Manager
Finance & HR	Finance & County Manager
Finance & Parks and Recreation	Finance & Planning
Social Services & HR	Veteran Services & Information Technology
Solid Waste and Recycling & HR	Elections & Emergency Services
Tax Administrator & HR	Elections & Information Technology
Tax Administrator & Library	Elections & County Manager
Tax Administrator & Finance	Animal Control & Emergency Services
Code Enforcement & HR	Soil and Water & Planning
Animal Control & HR	
MM>FM>MF>FF	**FM>MM>MF>FF**
Planning & Information Technology	Social Services & County Manager
Solid Waste and Recycling & Health	Sheriff & Social Services
Sheriff & Health	Tax Administrator & Parks and Recreation
Tax Administrator & Planning	Tax Administrator & Veteran Services
Tax Administrator & Social Services	Animal Control & Tax Administrator
Code Enforcement & Tax Administrator	Animal Control & Code Enforcement
Animal Control & Finance	Soil and Water & HR
Soil and Water & Health	Soil and Water & Finance
Soil and Water & Solid Waste and Recycling	
FF>MM>FM>MF	**MM>MF>FM>FF**
County Manager & Health	Parks and Recreation & Planning
Planning & County Manager	Social Services & Planning
Finance & Emergency Services	Veteran Services & Register of Deeds
Finance & Health	Airport & Health
Social Services & Health	Airport & Tax Administrator
Social Services & Information Technology	County Extension & Planning
Social Services & Parks and Recreation	County Extension & Parks and Recreation

of this pattern. The two gendering patterns in the second row, and in the second column of the third row, are more male centric, with both females and males exhibiting bias in favor of male recipients. Soil and Water, County Extension, Sheriff, and Social Services departments appear either exclusively or disproportionately within these patterns. Looking across gendering patterns, we see that the forms of bias exhibited in communication with managers of some departments, including Information Technology, Health, Tax Administrator and County Manager, depend upon the affiliation of the other manager in the dyad, as these departments are relatively evenly spread across gendering patterns.

There are several limitations involved with using the department affiliations of managers to operationalize domain. First, we need to combine dyads across counties to build domain-specific datasets, which involves the questionable assumption that managers from comparably named departments, but very different counties (e.g., urban/rural, wealthy/poor, coastal/Appalachian), perform similar governing functions. Second, this approach does not make use of the textual content in the e-mails, which is likely relevant to understanding the domain of communication. Our second analytical approach addresses the limitations associated with using department affiliation to measure the domain of communication.

Email Content as Domain

In our second analytical approach we use the content of emails to determine the domain of communication. This is a natural and flexible way of accounting for the domain of communication, as emails about different domains will typically have different content. However, the challenge with using the raw text to classify emails according to domain is that language use does not vary in a perfectly predictable manner across domains. As such, we use a statistical model that has been developed by Denny et al. [8] for application to text-valued interpersonal communication data, in order to infer domains from patterns of word co-occurence and sender-receiver interaction. The modeling framework we adopt represents a joint model of email content and content-specific network structure, which captures the content-conditional relationship between the gender of an email sender and the gender of its recipients.

A Model of Email Content. Denny et al.'s model jointly accounts for the structure and content of an observed email network by combining ideas from latent space network modeling [13] with ideas from statistical topic modeling [4]. This model treats the sender, recipients, and contents of each email as observed, and simultaneously infers latent topics of communication and content-based gender mixing patterns, extending Krafft et al.'s topic-partitioned multinetwork embeddings model [15].

Denny et al.'s model is a generative model; that is, it implies a particular probabilistic generative process, by which a corpus of emails could theoretically have been generated.

This generative process starts by generating the global (corpus-wide) variables. There are two main types of global variables: those that describe the topics people talk about and those that describe how people interact (interaction patterns). The former are a set of T topics. Each topic $\boldsymbol{\phi}^{(t)}$ is a discrete distribution over V word types. The latter are a set of C interaction patterns. Each interaction pattern consists of an intercept $b^{(c)} \in \mathbb{R}$, a coefficient vector $\boldsymbol{\gamma}^{(c)} \in \mathbb{R}^P$, and a set of A positions $\{\boldsymbol{s}_a^{(c)} \in \mathbb{R}^K\}_{a=1}^A$—one for each person. Each sender–recipient pair is also associated with an observed P-dimensional vector of covariates $\boldsymbol{x}^{(ar)}$; these covariates are not generated, however. Together these variables specify the (pattern-specific) probability of sender $a \in \{1, \ldots, A\}$ emailing recipient $r \neq a$: $p_{ar}^{(c)} = \sigma(b^{(c)} + \boldsymbol{\gamma}^{(c)\top} \boldsymbol{x}^{(ar)} - ||\boldsymbol{s}_a^{(c)} - \boldsymbol{s}_r^{(c)}||)$.

The topics and interaction patterns are linked via a set of T categorical variables. Each variable l_t associates the corresponding topic with a single interaction pattern that best describes how people interact when talking about that topic.

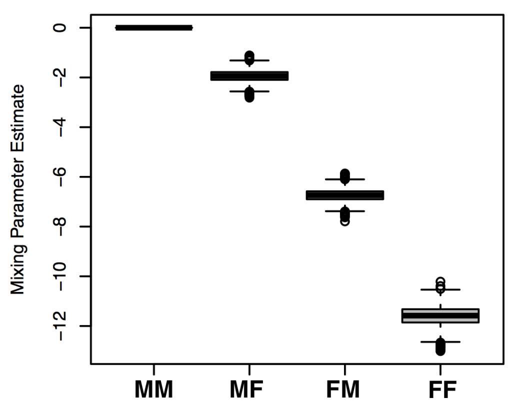
Next, the generative process generates the local (email-specific) variables. There are D emails. Each email's sender $a^{(d)} \in \{1, \ldots, A\}$ and length $N^{(d)} \in \mathbb{N}^0$ are not generated. First, each email is associated with a distribution $\boldsymbol{\theta}^{(d)}$ over the T topics. Each token $w_n^{(d)}$ in the email is generated by first

for $t = 1$ to T **do**
draw $\boldsymbol{\phi}^{(t)} \sim \mathrm{Dir}(\beta, \boldsymbol{n})$
end for
for $c = 1$ to C **do**
draw $b^{(c)} \sim \mathcal{N}(0, \sigma_1^2)$
draw $\boldsymbol{\gamma}^{(c)} \sim \mathcal{N}(\mathbf{0}, \sigma_2^2 \,\mathrm{I}_P)$
for $a = 1$ to A **do**
draw $\boldsymbol{s}_a^{(c)} \sim \mathcal{N}(\mathbf{0}, \sigma_3^2 \,\mathrm{I}_K)$
end for
for $a = 1$ to A **do**
for $r = 1$ to A **do**
if $r \neq a$ **then**
set $p_{ar}^{(c)} = \sigma(b^{(c)} + \boldsymbol{\gamma}^{(c)\top} \boldsymbol{x}^{(ar)} - ||\boldsymbol{s}_a^{(c)} - \boldsymbol{s}_r^{(c)}||)$
else
set $p_{ar}^{(c)} = 0$
end if
end for
end for
end for
for $t = 1$ to T **do**
draw $l_t \sim \mathrm{Unif}(1, C)$
end for
for $d = 1$ to D **do**
draw $\boldsymbol{\theta}^{(d)} \sim \mathrm{Dir}(\alpha, \boldsymbol{m})$
set $\bar{N}^{(d)} = \max(1, N^{(d)})$
for $n = 1$ to $\bar{N}^{(d)}$ **do**
draw $z_n^{(d)} \sim \boldsymbol{\theta}^{(d)}$
if $N^{(d)} \neq 0$ **then**
draw $w_n^{(d)} \sim \boldsymbol{\phi}^{(z_n^{(d)})}$
end if
end for
for $c = 1$ to C **do**
set $\bar{N}^{(c|d)} = \sum_{n=1}^{\bar{N}^{(d)}} \delta(l_{z_n^{(d)}} = c)$
end for
for $r = 1$ to A **do**
draw $y_r^{(d)} \sim \mathrm{Bern}(\sum_{c=1}^{C} \frac{\bar{N}^{(c|d)}}{\bar{N}^{(d)}} p_{a^{(d)}r}^{(c)})$
end for
end for

Fig. 2. Generative process for Denny et al.'s model.

for $i = 1$ to I **do**
for $d = 1$ to D **do**
for $n = 1$ to $N^{(d)}$ **do**
$z_n^{(d)} \sim P(z_n^{(d)} \,|\, \mathcal{B}, \Gamma, \mathcal{S}, \mathcal{L}, \mathcal{Z}_{\setminus d,n}, \mathcal{W}, \mathcal{Y}, \mathcal{X}, \mathcal{A})$
end for
end for
for $t = 1$ to T **do**
$l_t \sim P(l_t \,|\, \mathcal{B}, \Gamma, \mathcal{S}, \mathcal{L}_{\setminus t}, \mathcal{Z}, \mathcal{X}, \mathcal{A})$
end for
$\mathcal{B}, \Gamma, \mathcal{S} \sim P(\mathcal{B}, \Gamma, \mathcal{S} \,|\, \mathcal{L}, \mathcal{Z}, \mathcal{Y}, \mathcal{X}, \mathcal{A})$
end for

Fig. 3. Block Metropolis-within-Gibbs inference algorithm for Denny et al's model.



Coding	Topic top words
Sandy	will, track, winds, system, forecast
Sandy	storm, sandy, high, coastal, tides, night
Harbor	status, update, boat, today, weather
Planning	board, meeting, planning, seafood, hearing
Storm	box, planning, director, permit, building

Fig. 4. Mixing parameter estimates and topic top words for the hurricane related interaction pattern in Dare county. Topics are presented (one per line) in decreasing order of use within the interaction pattern, as are words within each topic. The hand coding procedure is discussed below.

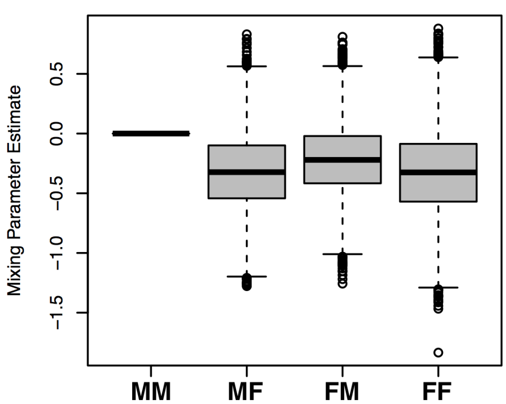
drawing a topic $z_n^{(d)}$ from this distribution and then drawing a word type from the topic's discrete distribution $\boldsymbol{\phi}^{(z_n^{(d)})}$. Having generated the email's contents, the generative process then proceeds by generating its recipients. For each possible recipient $r \neq a^{(d)}$, a binary variable $y_r^{(d)}$ is generated indicating whether or not the email is sent to that recipient. This variable is drawn from a Bernoulli distribution, parameterized by a mixture of pattern-specific probabilities: $\sum_{c=1}^{C} \frac{\bar{N}^{(c|d)}}{\bar{N}^{(d)}} p_{a^{(d)}r}^{(c)}$. The normalized mixing weight $\frac{\bar{N}^{(c|d)}}{\bar{N}^{(d)}}$ for interaction pattern c is the proportion of tokens in that email associated with (a topic associated with) pattern c. As a result, the email's recipients depend on the topics expressed within it and, in turn, on the interaction patterns associated with those topics.

This generative process implies a particular factorization of the joint distribution over $\Phi = \{\boldsymbol{\phi}^{(t)}\}_{t=1}^{T}$, $\mathcal{B} = \{b^{(c)}\}_{c=1}^{C}$, $\Gamma = \{\boldsymbol{\gamma}^{(c)}\}_{c=1}^{C}$, $\mathcal{S} = \{\{\boldsymbol{s}_a^{(c)}\}\}_{c=1}^{C}$, $\mathcal{L} = \{l_t\}_{t=1}^{T}$, $\Theta = \{\boldsymbol{\theta}^{(d)}\}_{d=1}^{D}$, $\mathcal{Z} = \{\boldsymbol{z}^{(d)}\}_{d=1}^{D}$, $\mathcal{W} = \{\boldsymbol{w}^{(d)}\}_{d=1}^{D}$, and $\mathcal{Y} = \{\boldsymbol{y}^{(d)}\}_{d=1}^{D}$ given $\mathcal{X} = \{\{\boldsymbol{x}^{(ar)}\}_{r=1}^{A}\}_{a=1}^{A}$, $\mathcal{A} = \{a^{(d)}\}_{d=1}^{D}$, and $\mathcal{N} = \{N^{(d)}\}_{d=1}^{D}$. The complete generative process is provided in figure 2.

Inference. For real-world email networks, we must invert the generative process described in the previous section to infer plausible values for the latent variables Φ, $\mathcal{B}$, Γ, $\mathcal{S}$, $\mathcal{L}$, Θ, and $\mathcal{Z}$. Denny et al. achieve this goal by integrating out Φ and Θ and then drawing samples from the posterior distribution over $\mathcal{B}$, Γ, $\mathcal{S}$, $\mathcal{L}$, and $\mathcal{Z}$ given $\mathcal{W}$, $\mathcal{Y}$, $\mathcal{X}$, and $\mathcal{A}$. Specifically, they define a Metropolis-within-Gibbs algorithm, in which each iteration involves sequentially resampling the value of each $z_n^{(d)}$ variable from its conditional posterior distribution, sequentially resampling the value of each l_t variable similarly, and then jointly sampling the values of $\mathcal{B}$, Γ, and $\mathcal{S}$ using the Metropolis algorithm. This procedure is outlined in figure 3.

We applied Denny et al.'s model separately to the email data from each county and then aggregated the model results. We used uniform base measures for the Dirichlet priors and set $\alpha = 1$ and $\beta = 0.01V$, where V is the length of the vocabulary for each county. We also set $\sigma_1^2 = \sigma_2^2 = \sigma_3^2 = 5$. We used forty topics and four clusters, to provide reasonable granularity in capturing variation in content, while making sure that the interaction patterns were interpretable and did not exhibit redundancy. We used the same values for all counties. Since our goal was to study gendered communication, we used four binary gender mixing covariates (i.e., MM, MF, FM, and FF). To ensure identifiability and interpretability of the coefficients Γ, we fixed the coefficient for the MM covariate to zero.

For each county, we ran Denny et al's inference algorithm for 4,000 iterations. This was sufficient to reach convergence (indicated by Geweke statistics) for all counties. To ensure mixing of Denny et al's inference algorithm, we draw 1,000 samples of $\mathcal{B}$, Γ, $\mathcal{S}$ during each iteration (line 10). After the 4,000 iterations, we fixed the values of $\mathcal{Z}$ and $\mathcal{L}$ and resampled the remaining variables for an additional 10,000,000 iterations.



Coding	Topic top words
IT	junk, box, summary, emails, login
Public Works	description, cell, director, works, public
Health	pharmacist, good, morning, schedule
Emergency	communications, emergency, status
HR	box, director, fax, work, address, payroll

Fig. 5. Mixing parameter estimates and topic top words for the selected interaction pattern in Dare county. Topics are presented (one per line) in decreasing order of use within the interaction pattern, as are words within each topic. The hand coding procedure is discussed below.

Analysis. Denny et al.'s model produces three key outputs that will be useful to an analysis of content specific patterns of gender mixing in communication. First, it infers a set of forty topics of communication for each county. These topics are distributions over words, and are commonly summarized by listing the words that have the highest posterior probability of being assigned to that topic. For example, a law enforcement topic might have the following top ten words: *safety, police, law, training, jail, enforcement, local, firearm, crime, corrections.* Denny et al.'s model also associates each topic with one of four interaction patterns. Finally, a set of gender mixing parameters is inferred for each interaction pattern. Therefore, we can use the mixing parameter estimates and associated topic top-words inferred by the model as ingredients in an analysis that is similar to our analysis using department as a proxy for the domain of communication.

Before diving into this analysis, we provide a few examples of model output. Our data collection window happend to overlap with Hurricane Sandy (October, 2013), and one of the counties in our sample (Dare county) is located on the coast, so we might expect there to be some hurricane related topics in our model output. As illustrated in figure 4, our model infers an interaction pattern where a number of the associated topics are related to Hurricane Sandy. We can see from the mixing parameter plot that this interaction pattern is strongly male-centric. This makes sense, given that the emergency managers and county manager in Dare county are all male. In contrast to the above example, other interaction patterns display no discernable gender bias. This is well illustrated by the interaction pattern presented in figure 5 from Hoke county.

For our analysis, we seek to construct a table similar to table 6, but now we relate rank-orderings of inferred gender-mixing parameters to topics associated with them. To do this, we first rank-order the mixing parameter estimates in each interaction pattern, for each county. We then discard those interaction pattern observations where we fail to reject the null hypothesis that all mixing parameters are equal. We then examine the topics from those interaction pattern which display one of the six most prevalent rank orderings of gender mixing parameters, as determined by the total number of tokens assigned to all topics in all interaction patterns associated with a particular rank ordering. Table 7 displays the three topics which have the largest number of tokens assigned to them, from each of the interaction patterns associated with each of the six most prevalent gender mixing parameter rank orderings. The gender mixing patterns are displayed in descending

[3] We compared this approach to simply weighting documents based on the number of tokens assigned to the topic, or the proportion of tokens assigned to the topic, and we found that it yields more interpretable emails.

order of the total number of tokens that were assigned to all topics associated with them (from top left to bottom right, by rows). Note that in this analysis, we only make use of data from sixteen counties, as the email data from Caldwell county did not contain a sufficient number of tokens per email (after preprocessing) to facilitate interpretation of model results.

In addition to displaying the top words associated with each topic, we assigned a hand-coded label to each topic using the following procedure. First, for each topic (which is specific to a county) we calculated a weight for each email based on the representation of that topic in the email using the following weighting scheme.

$$\omega_t^{(d)} = \frac{\left(N_t^{(d)}\right)^2}{N^{(d)}} \qquad [1]$$

In words, the weight we assign each document is equal to the proportion of tokens in that email that are assigned to the topic, times the number of tokens in that email assigned to the topic. This gives the highest weight to long emails that contain a high proportion of tokens assigned to the topic[3]. We then selected the ten highest weight emails and read them, before assigning a label to the topic. This hand coding was performed by one member of our team, and a label was selected using the following criterion: the coder selected a word or phrase that best summarized the common thread between the emails, unless no common thread was detected, in which case the topic was labeled as a junk topic. In practice, these labels most often reflected what we have termed a domain of communication. For example, the ten emails associated with a topic labeled *finance* might all involve other department managers emailing back and forth with the finance manager to ask them about the proper procedures for purchasing supplies. Alternatively, they might involve the finance department manager emailing with other department managers to clarify budget items and their expectations for their funding needs in the coming fiscal year. A small proportion of topics were associated with emails about some particular event, like managers emailing each other to see if they were all safe after Hurricane Sandy, that did not specifically relate to an organizational function.

The most frequently observed gender mixing pattern exhibits gender heterophily (FM > MF > FF > MM), and does not exhibit a systematic pattern in the topics associated with it. The second most frequently observed gender mixing pattern is male-centric (MM > FM > MF > FF), and is associated with a higher proportion of topics related to planning and public works projects than the other gender mixing patterns. Perhaps most interestingly, the two female-centric gender mixing patterns (FF > FM > MF > MM and FF > MF > FM > MM) are both associated with a large proportion of topics related to finance and HR. Recent findings by Dasgupta et al. [7] suggest we should expect more female-centric interaction patterns in domains with greater representation of women, and the finance and HR departments are both primarily managed by women. Thus our results seem to agree with this finding.

Conclusion

Interactions between employees of an organization represent the building blocks of fundamental processes that drive employee and organizational performance, such as leadership, collaboration, and competition. Communication is a ubiquitous form of intra-organizational interaction. In the current paper we study electronic communication within local government organizations, with the goal of identifying domain-specific patterns of gender-dependent interaction. Using internal e-mail corpora covering department managers in seventeen North Carolina counties, we find that the specific forms of gender dependence vary widely across domains. Using two distinct analytical approaches, we find robust patterns in terms of how interaction depends upon gender across domains. Specifically, in communications relevant to finance and human resources, we find female-centric interaction patterns, in which both males and females are more likely to direct their communications to females than to males. Given that the finance and HR department managers in our sample are overwhelmingly female, our results agree with recent findings in the literature indicating that females are more active in small groups when the groups are majority female.

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References

1. Susan M Adams, Atul Gupta, Dominique M Haughton, and John D Leeth. Gender differences in ceo compensation: evidence from the usa. *Women in Management Review*, 22(3):208–224, 2007.
2. James Albrecht, Anders Björklund, and Susan Vroman. Is there a glass ceiling in Sweden? *Journal of Labor Economics*, 21(1):145–177, 2003.
3. William T. Bielby and James N. Baron. Men and Women at Work : Sex Segregation and Statistical Discrimination. *American Journal of Sociology*, 91(4):759–799, 1986.
4. DM Blei, AY Ng, and MI Jordan. Latent dirichlet allocation. *The Journal of Machine Learning Research*, 3:993–1022, 2003.
5. Daniel J. Brass. Men's and Women's Networks: A Study of Interaction Patterns and Influence in an Organization. *Academy of Management Journal*, 28(2):327–343, 1985.
6. Emilio J Castilla. Gender, race, and meritocracy in organizational careers. In *Academy of Management Proceedings*, volume 2005, pages G1–G6. Academy of Management, 2005.
7. Nilanjana Dasgupta, Melissa McManus Scircle, and Matthew Hunsinger. Female peers in small work groups enhance women's motivation, verbal participation, and career aspirations in engineering. *Proceedings of the National Academy of Sciences*, page 201422822, 2015.
8. Matthew J. Denny, Hanna Wallach, and Bruce A. Desmarais. Hierarchical topic-partitioned multinetwork embeddings: Modeling social structure and content across a sample of communication networks. In *International Conference on Computational Social Science , Helsinki*, 2015.
9. Colin Duncan and Wendy Loretto. Never the Right Age? Gender and Age-Based Discrimination in Employment. *Gender, Work & Organization*, 11(1):95–115, 2004.
10. Kim M Elsesser and Janet Lever. Does gender bias against female leaders persist? quantitative and qualitative data from a large-scale survey. *Human Relations*, 64(12):1555–1578, 2011.
11. Robin J Ely and Debra E Meyerson. Theories of gender in organizations: A new approach to organizational analysis and change. *Research in organizational behavior*, 22:103–151, 2000.
12. Jenny Rose Finkel, Trond Grenager, and Christopher Manning. Incorporating non-local information into information extraction systems by gibbs sampling. In *Proceedings of the 43rd Annual Meeting on Association for Computational Linguistics*, ACL '05, pages 363–370, Stroudsburg, PA, USA, 2005. Association for Computational Linguistics.
13. Peter D Hoff, Adrian E Raftery, and Mark S Handcock. Latent Space Approaches to Social Network Anal-

ysis. *Journal of the American Statistical Association*, 97(460):1090–1098, December 2002.

14. Herminia Ibarra. Homophily and Differential Returns : Sex Differences in Network Structure and Access in an Advertising Firm. *Administrative Sceince Quarterly*, 37:422–447, 1992.
15. Peter Krafft, Juston Moore, Bruce A Desmarais, and Hanna Wallach. Topic-partitioned multinetwork embeddings. In *Advances in Neural Information Processing Systems Twenty-Five*, 2012.
16. Christopher D. Manning, Mihai Surdeanu, John Bauer, Jenny Finkel, Steven J. Bethard, and David McClosky. The Stanford CoreNLP natural language processing toolkit. In *Proceedings of 52nd Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, pages 55–60, 2014.
17. Belle Rose Ragins and Eric Sundstrom. Gender and Power in Organizations: A Longitudinal Perspective. *Psychological Bulletin*, 105(1):51–88, 1989.

Table 7. Hand coded topic labels, and Topic top-words (one topic per line) for the three topics with the greatest N_t in each cluster, for each cluster associated with each gender mixing parameter ordering.

Coding	FM > MF > FF > MM
Emergency	fire, cell, drawer, contract, marshal, fax
Elections	public, board, director, email, address, box
Public Works	water, department, director, meter, kill
Health	class, benefits, plan, insurance, enrollment
HR	safety, management, understanding, training, law
Junk	office, good, airport, call, meeting, fax, time
IT	junk, box, summary, emails, report, personal, visit
Public Works	director, communications, emergency, central
Outreach	health, navigation, attached, main, read
Transit	e-mail, received, intended, confidential, error
IT	law, box, enforcement, e-mail, records, subject
Finance	office, finance, wrote, oct, tue, meeting, nov
HR	employees, time, on-call, tax, exempt, wrote, work
Budget	budget, year, meeting, board, employee, cost, july
Tax	ordinance, changes, manager, email, send, additional
Planning	meeting, economic, development, planning, office
Emergency	message, e-mail, intended, attachments
Manager	main, street, east, fax, manager, office, meeting

Coding	MM > FM > MF > FF
Finance	finance, director, fax, phone, ext, cpa, letter
Finance	insurance, renewal, liability, fax, director
Soc. Serv.	good, services, director, exercise, department
Manager	office, work, time, meeting, today, monday
HR/Manager	leave, work, week, time, pay, years, good
IT	electronic, mail, intended, error, received, recipient
Manager	office, email, time, staff, meeting, work, good
IT	electronic, mail, intended, email, message, recipient
Health	health, department, project, email, code, garden
Junk	e-mail, intended, confidential, error, received
Comments	jail, mobile, inmates, ago, money, jails
Elections	meeting, e-mail, time, wrote, dec, good, letter
Library	library, fort, time, book, story, thursday
Library	books, april, free, friends, songs, sale, saturday
Planning	east, planning, street, court, administrator, ext
Tourism	fort, year, director, street, full, main, holiday
Animal	outreach, call, animals, inspection, works, public
HR	time, work, issue, full, going, position, hours, budget
Public Works	public, nashville, suite, washington
Public Works	email, energy, carolina, north, address
Public Works	public, nashville, chiller, washington
Planning	description, director, street, church, suite
Planning	description, fax, phone, director, street, church
Zoning	board, meeting, planning, amendment, commissioners
Emergency	operations, emergency, director, lines, street
Development	description, director, development, projects
Tax	office, attached, bill, amount, year, motor, program

Coding	FF > FM > MF > MM
Finance	order, time, good, april, attached, requests
Finance	budget, phone, finance, media, ext, department
Health	meeting, going, fyi, tricaster, health, project
Finance	meeting, box, fax, finance, attached, resolution
Finance	equity, fax, debt, refunding, time, finance, call
Finance	debt, box, fax, finance, policies, contract, audit
Finance	learn, leader, director, washington, dream
Finance	fax, ext, phone, finance, director, street
Finance	washington, street, finance, actions, inspire, ext
Health	public, health, email, department, contact
Health	public, health, email, contact, disclosure
Finance	good, time, increase, call, pay, office, today
Manager	fax, east, street, office, main, manager, fyi
Budget	manager, street, main, fax, office, east, budget
Budget	fund, budget, balance, year, funds, pay, original

Coding	MF > FM > FF > MM
HR	class, benefits, plan, insurance, enrollment, benefit
Planning	planning, department, box, phone, planner/section
HR	safety, understanding, management, law, enforcement
Spam	computer, excellent, work, opportunity, applicants
Inspections	code, director, office, enforcement
Extension	extension, good, road, program, wrote, suite
Finance	requisition, approval, munis, department, pending
Manager	manager, meeting, employees, project, plan, impact
Finance	contract, copy, grant, additional, finance

Coding	FF > MF > FM > MM
Finance/HR	dss, office, time, cost, allocation, finance
Finance	budget, park, year, salaries, water, bethlehem
IT	password, change, reminder, expires, account, days
Emergency	director, phone, report, fax, emergency
Finance	transportation, public, director, legion, read
HR	read, year, fiscal, worker, audit, comp, increase
Planning	public, email, manager, box, board, attorney, law
HR	director, box, planning, phone, fax, resources, human
Hurricane	monday, fund, hurricane, island, water, winds
Finance	public, mail, electronic, message, time, review
HR	director, letter, bill, copy, years, june, position
Inspections	library, property, people, time, list
Utilities	public, utilities, facilities, director
Finance	water, loss, unaccounted, report, gallons, amount
Finance	balance, finance, fund, box, officer, read
HR	policy, office, emergency, director, services, time
Finance	center, rural, recreation, grant, director
Tax	tax, administrator, library, year, extension, budget

Coding	MM > FF > MF > FM
HR	class, benefits, plan, insurance, enrollment, benefit
HR	planning, director, department, meeting, fax, box
HR	safety, management, understanding, training, law
Soc. Serv.	intended, message, services, e-mail
Extension	area, extension, cooperative, street, court
Finance	style, questions, span, revenue, fund, week
Finance	recipient, attachments, services, requested, email
Emergency	office, cell, email, fax, services, emergency
Finance/HR	time, call, morning, budget, changes, payroll
Health	health, phone, subject, public, address, third
Health	health, phone, director, public, disclosed
Budget	tuesday, july, animal, commissioners, money
Health	health, department, street, tel, mph, college
Finance	pending, finance, letter, case, director, office
Finance	requisition, approval, munis, department, pending