**Madhuri Vempati**
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September 15, 2026

Workshop on Development Economics and Networks for Early-Stage Researchers, Fall 2026
National Bureau of Economic Research
1050 Massachusetts Avenue, Cambridge, MA 02138

Dear Professors Breza, Chandrasekhar, and Viviano,

I am writing to apply to present at the Workshop on Development Economics and Networks for Early-Stage Researchers, to be held on December 5, 2026. I am a fourth-year PhD candidate in Economics at Columbia University, working in labor and organizational economics with a focus on Bangladesh. My dissertation research uses field and administrative data from Bangladeshi garment factories to study how incentive design, team and network composition, and monitoring systems shape worker effort, safety, and career outcomes.

Enclosed with this application are my curriculum vitae, a brief statement of my research interests and motivation for attending, and an extended abstract for the paper titled "Workplace Networks and Productivity: Evidence from Garment Factories" (co-authored with Uditi Karna, Laura Boudreau, Sakib Mahmood, and Oren Reshef), which I would welcome the opportunity to present. My coauthor, Uditi Karna, is also submitting a separate application to this workshop, and we would like to present this work jointly if that is possible.

My advisors, Eric Verhoogen, Professor, Department of Economics and School of International and Public Affairs, Columbia University (eric.verhoogen at columbia dot edu), and Laura Boudreau, Gantcher Associate Professor of Economics, Graduate School of Business, Columbia University (l.boudreau at columbia dot edu), have agreed to provide a letter of recommendation should I be shortlisted for participation.

Thank you for considering my application. I would very much value the opportunity to share this work and receive feedback from the workshop community.

Sincerely,
Madhuri Vempati

# Madhuri Vempati

Last Updated: Sep 2026

CONTACT INFORMATION

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## EDUCATION

**Columbia University, New York, NY**
Ph.D. in Economics — 2023-2029 (Expected)
M.Phil. in Economics — 2026
M.A. in Economics — 2025

**Purdue University, West Lafayette, IN**
B.S. in Mathematics - Computer Science
B.S. in Economics - Honors — 2023

## COURSEWORK

**Core:** Microeconomic Analysis I and II, Macroeconomic Analysis I and II, Introduction to Econometrics I and II, Math Methods for Economists, Perspectives on Economic Studies

**Field:** Frontiers of Macroeconomics, Topics in Development Economics, Economics of Labor I, Theory of Internal Trade, Public Economics and Development, Industrial Organization I, Topics in Organizational Economics, Industrial Development, Colloquium in Development, Labor and Public Finance Colloquium

## WORKS IN PROGRESS

**Workplace Networks and Productivity: Evidence from Garment Factories** — 2025–Present
*with Laura Boudreau, Uditi Karna, Sakib Mahmood, and Oren Reshef*

**Organizational Capacity Building and Firms' Safety Culture: Evidence from the Nirapon Safety Management Program in Bangladesh** — 2025–Present
*with Laura Boudreau and Sakib Mahmood*

**Authority Without Consent** (Pilot Stage) — Mar 2026–Present

## RESEARCH AND WORK EXPERIENCE

**Research Assistant, Columbia University** — Summer 2025-Present
*"Social Norms and Worker Productivity" under advisor Laura Boudreau*

- Analyze a field experiment in six Bangladeshi knitwear factories examining how gender- and age-based social hierarchies shape knowledge transmission and skill adoption, drawing on surveys, skill training + assessments, and daily production records for approximately 6,900 workers.
- Clean and merge survey data; analyze Becker–DeGroot–Marschak elicitation data to estimate workers' willingness to pay for instruction from male versus female peers and reservation wages for instructing male versus female peers, examining heterogeneity by worker gender and the public visibility of choices.

- Harmonize daily production, attendance, and garment-style records; estimate the direct and spillover effects of skills training on task variety, production efficiency, and productivity, with attention to gender heterogeneity.

## TEACHING EXPERIENCE

**Teaching Fellow, Columbia University**

| | |
|---|---|
| Introduction to Econometrics (Undergraduate Core) | Fall 2026 |
| Economics of NYC (Undergraduate) | Spring 2026 |
| Principles of Economics (Undergraduate) | Spring 2025, Fall 2026 |
| Math Methods for Economists (MA) | Fall 2024 |

**Undergraduate Teaching Assistant, Purdue University**

| | |
|---|---|
| Lead TA - Ordinary Differential Equations | Fall 2022 |
| Ordinary Differential Equations (3 semesters) | 2021-2022 |

## HONORS AND AWARDS

| | |
|---|---|
| Dean's Fellowship, Columbia University | 2023-2024 |
| Alton D. and Juanita S. Andrews Memorial Scholarship | 2022-2023 |
| Thomas Arai Scholarship | 2022-2023 |
| Alton D. and Juanita S. Andrews Memorial Scholarship | 2021-2022 |
| Dean's List, Purdue University | 2019-2023 |

## TECHNICAL SKILLS

| | |
|---|---|
| *Computer Languages and Software* | C/C++, Java, Python, R, STATA, MATLAB, Julia, SQL, LaTeX |
| *Languages* | English (native speaker)<br>Telugu (working proficiency)<br>Hindi (working proficiency)<br>Arabic (proficient listening, reading and writing) |

## MISCELLEANEOUS

Citizenship: India

## REFERENCES

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**Research Statement**

*Madhuri Vempati, PhD Student, Columbia University*

Workshop on Development Economics and Networks for Early-Stage Researchers, Fall 2026

My research interests lie at the intersection of development, organizational, and labor economics, with a particular focus on how workplace institutions and social relationships shape worker productivity, career progression, and inequality in low- and middle-income countries. I am especially interested in understanding how firms can improve organizational performance through changes in managerial practices, personnel policies, and the structure of interactions among workers.

One strand of my research examines managerial authority and organizational design. My current project in Bangladesh studies whether the realization of managerial authority can be shaped by the way firms select and communicate managerial appointments. The project is currently in the pilot stage and plans to experimentally vary transparency about manager selection and the degree of discretion given to managers, allowing me to study whether workers are more willing to comply, exert effort, and cooperate when managerial authority is perceived as procedurally fair. More broadly, this work asks how organizational practices interact with beliefs and informal relationships in settings where employment relationships are difficult to govern entirely through contracts. My other work with garment firms in Bangladesh considers how firms respond to safety incentives, information, and capacity building initiatives, and how these interventions affect both long-term workplace practices and workers' well-being.

A second strand of my research studies the role of social networks within firms. In ongoing work with Boudreau, Karna, Mahmood, and Reshef, we leverage worker-level network and productivity data collected as part of a randomized experiment in Bangladeshi sweater firms (Boudreau et al., 2022). The project examines how horizontal workplace relationships develop and whether access to more productive or central peers affects workers' longer-run productivity and career outcomes. We also study the role of spatial and temporal proximity in shaping workplace relationships, as well as whether unequal access to productive peers contributes to subsequent gender gaps in workplace outcomes. This will be the topic we hope to discuss at the workshop.

We are applying to the Workshop on Development Economics and Networks for Early-Stage Researchers as this project sits squarely at that intersection, using network measurement tools developed in the aggregated relational data literature to study a substantive development and labor question. We are at a stage where feedback on identification strategy – particularly on separating peer effects from sorting and reflection – would be especially valuable, and I would welcome the chance to learn from other early-stage researchers and from the organizers' own work on networks in development settings.

References:

Boudreau, L., Mahmood, S., & Reshef, O. (2022). Social Norms and Firm Productivity: Evidence from Bangladeshi Knitwear Factories [Dataset]. In *AEA Randomized Controlled Trials*. https://doi.org/10.1257/rct.9548-1.2

# Workplace Networks and Productivity: Evidence from Garment Factories

Laura Boudreau[*], Uditi Karna[†], Sakib Mahmood[‡], Oren Reshef[§], and Madhuri Vempati[¶]

September 2026

**Abstract**

Workers rely heavily on social connections for information, support, and economic opportunities, particularly in low-income labor markets. Yet relatively little is known about how workplace ties shape worker performance and whether unequal network structures contribute to gender gaps. We study these questions using approximately 4,600 machine operators in five Bangladeshi sweater factories, combining friendship nominations, relational data, workers' spatial locations, and daily production and personnel records. Workplace networks are strongly gendered and spatially concentrated: men have substantially larger networks than women, and workers on the same production line are much more likely to be friends. Workers' productivity and exit are also strongly correlated with the productivity and exit of their friends, suggesting that workplace ties are closely linked to longer-run worker outcomes. Exploiting the staggered introduction of new garment components, we find that an additional early same-line friend predicts approximately 2.4 percent higher performance when a worker first begins a garment, significantly more than exposure to either same-line non-friends or off-line friends. Friendship also predicts faster subsequent learning, including across production lines, consistent with information transmission beyond contemporaneous co-presence. Together, the results show that workplace networks shape production and retention and highlight unequal access to productive peers as a potential channel for gender differences in longer-run outcomes.

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## 1. Introduction

Social relationships are a pervasive feature of the workplace, but their consequences need not be equally distributed across workers. A growing body of work shows that *vertical* social ties to supervisors and managers shape careers: employees with more face-to-face interaction with their managers are promoted faster and see improved career outcomes (Cullen and Perez-Truglia, 2023). This paper asks whether an analogous role is played by *horizontal* social ties among coworkers, as distinct from these vertical ties. Horizontal relationships operate through peer-to-peer channels such as direct learning and skill transfer, mutual effort coordination, peer competition or social pressure, and informal social insurance against workplace shocks. This contrasts with the vertical channels through which supervisors shape careers, such as managerial advocacy and access to high-value assignments. If workers differ systematically in whom they are connected to, horizontal relationships can generate persistent differences in workplace performance and career progression even among workers performing the same jobs. In particular, we ask two questions: Do horizontal social ties affect worker productivity and longer-run employment outcomes? And through what mechanisms do these relationships operate?

We study machine operators in sweater factories in Bangladesh. Our sample is drawn from the linking department, the largest department in these factories. Here, men and women perform the same production activities, and women constitute approximately 36% of our sample (Table 1). This setting is well suited to studying horizontal social ties for two reasons. First, production is individual and piece-rate. Workers are compensated according to their own output rather than team output, so the setting avoids the mechanically correlated outcomes that arise under team-based pay, and it differs from relative-incentive pay schemes such as that studied by Bandiera et al. (2005), in which one worker's output can impose a negative externality on the pay of coworkers performing the same task. At the same time, production is highly spatial, workers are organized across floors and production lines and repeatedly interact with coworkers located nearby, generating substantial variation in opportunities for social interaction. In addition, we combine rich administrative records, including the spatial distribution of workers across production lines, with novel survey data on horizontal social networks, described in detail below.

We combine an especially rich set of data collected as part of a randomized evaluation by Boudreau et al. (2022). First, a detailed network survey asks workers to nominate their *three* closest workplace friends, allowing us to observe the identities and characteristics of workers' salient horizontal relationships. Second, following Breza et al. (2020), aggregated relational data (ARD) elicit unrestricted measures of workers' broader workplace networks. Third, production and administrative records allow us to follow individual productivity, retention, and career progression over a substantially longer horizon than is typically available in studies of workplace social interactions. Finally, detailed records of workers' locations within the factory allow us to map these social relationships onto production floors and lines and, in ongoing work, to workers' positions within lines. This combination, direct friendship nominations, ARD measures, spatial workplace data, and high-frequency administrative outcomes on the same workforce, is highly unusual in the literature

on workplace social networks, and allows us to distinguish the structure of workers' social networks from the set of coworkers to whom they are simply exposed.

The descriptive patterns reveal that workplace networks vary systematically with gender, age, and tenure, while religion exhibits little meaningful variation in this setting (Table 1). Gender differences are particularly pronounced: men receive 2.09 friendship nominations on average, compared with 1.36 among women, despite very similar age and tenure. Network connectedness also increases with tenure and, more modestly, with age. Friendships are highly spatially structured, with ties concentrated among workers on the same production line. Comparing pairs of workers, those assigned to the same production line are approximately 7 percentage points more likely to be friends than workers assigned to different lines, even after accounting for when they joined and demographic similarity. This difference is large relative to the overall probability that any two workers are friends, which is only 0.64% (Table 4). These patterns imply that gender and spatial exposure jointly determine which productive coworkers workers can access through their social networks.

Production proceeds through successive garment runs, with workers starting new styles and components at different points in the production cycle. As a result, some coworkers already have garment-specific experience when others begin. Our current results suggest that the structure of workplace networks is meaningfully related to worker outcomes. Workers' own efficiency and likelihood of exit are both strongly correlated with the efficiency of their same-line friends, with higher same-line friend efficiency predicting higher own efficiency and a lower own exit probability (Table 6); because friends may simply share similar ability or common shocks, we do not interpret this raw correlation causally. Exploiting the staggered timing above, we find that an additional early same-line friend predicts significantly higher entry performance than either a same-line non-friend or an off-line friend, while early friends, whether on or off the line, predict faster subsequent learning (Table 10); the same-line specificity of the entry-performance result, together with its absence for learning, points to distinct mechanisms across the two margins. Fully distinguishing peer influence from sorting and common shocks, rather than only quantifying its contribution to existing gaps, remains the central objective of the identification strategy described in Section 2.

Our contribution relates to three strands of the literature. First, we contribute to work on the role of social interactions and social ties at work (Mas and Moretti, 2009; Bandiera et al., 2005, 2010; Cornelissen et al., 2017; Park, 2019; Sandvik et al., 2020; Menzel, 2021; Emanuel et al., 2026; Hamilton et al., 2003). Most closely, Bandiera et al. (2010) combine friendship data with individual piece-rate production records and show that workers adjust short-run effort, over daily to weekly production spells, when working alongside friends of different ability. In contrast, we study horizontal relationships over a substantially longer horizon, extend the outcomes from contemporaneous productivity to retention and career progression, and ask how the structure of these relationships generates differential outcomes for men and women. Second, we contribute to the literature on gender gaps within firms and workplaces (Bertrand et al., 2010; Cullen and Perez-Truglia, 2023; Benson et al., 2026; Hampole et al., 2026). Cullen and Perez-Truglia (2023)

show that gender differences in *vertical* social interactions with managers affect promotion and pay through differential access to career opportunities, while Hampole et al. (2026) show that peer composition can affect women's longer-run advancement into corporate leadership. We study the corresponding role of *horizontal* relationships among coworkers and emphasize a distinct mechanism: gendered network structure can generate unequal access to productive peers and thereby contribute directly to gaps in performance as well as subsequent workplace outcomes. Third, we contribute to the economics of social networks (Munshi, 2003; Banerjee et al., 2013; Alatas et al., 2016; Breza et al., 2020). We bring the ARD approach into the workplace, where many interactions among coworkers occur outside formal contracting, and combine it with direct friendship nominations, spatial data, and administrative measures of performance. In doing so, we show that the *structure and composition* of workers' networks, rather than simply whether social ties exist, are predictive of workplace performance and can contribute systematically to gender differences in workplace outcomes.

## 2. Data and Descriptives

We study five sweater factories in Bangladesh, comprising approximately 4,600 workers. The data combine a survey in which each worker named up to three of her closest workplace friends with daily worker-level production records. The survey also includes an aggregated relational data (ARD) module in which workers report their total friend count and its composition along several traits. The measures used throughout, such as friendship ties and each worker's nomination in-degree and out-degree, are constructed from the capped nomination roster. Throughout the analysis, a *garment* is defined as a factory-specific style paired with a cleaned production-component group, where a style denotes the specific garment design being produced and a component denotes a distinct sewing or assembly operation performed on it.

Workplace friendship networks are small and strongly gender-segregated despite the similarity of male and female workers along observable characteristics. Among the longest-tenured workers, men make an average of 2.62 friendship nominations compared with 2.31 among women; the corresponding gap in incoming nominations is larger, at 3.40 versus 1.88 (Table 2). The observed same-gender friendship rate exceeds the random-mixing benchmark by 29.6 percentage points, substantially more than the corresponding excess homophily by tenure (11.7 percentage points) or age (8.5 percentage points) (Table 3). These patterns generate substantial gender differences in access to workplace peers and provide a potential horizontal-network channel for gender differences in workplace outcomes.

Tie formation is also highly spatial. Workers assigned to the same production line are 7.0 percentage points more likely to be friends than workers on different lines, more than ten times the unconditional dyadic friendship rate of 0.64 percent (Table 4). We interpret this pattern differently from the demographic measures above. Unlike gender, age, or tenure, floor assignment primarily determines opportunities for repeated interaction rather than reflecting preference-based sorting. We also find that entry timing predicts friendship only over a narrow and decaying window. The

association is 0.29 percentage points at one month and declines to 0.06 percentage points by twelve months. Once entry timing is interacted with same-line status, its direct effect largely disappears, while the interaction is large (2.4 percentage points) and highly significant (Table 5). Thus, common entry timing alone does not predict tie formation; rather, it identifies a period in which ties are substantially more likely to form among workers who are also spatially co-present. These patterns motivate an empirical design centered on *line* and *timing of exposure*.

Workers' productivity and retention are also correlated within their friendship networks: an additional standard deviation in the average efficiency of a worker's same-line friends predicts a 0.243 standard deviation increase in her own efficiency, and is associated with a lower likelihood of exit (Table 6). Notably, off-line non-friends exhibit a similarly strong correlation with own efficiency, underscoring that this raw pattern need not be specific to friendship.

Taken together, these descriptives establish that workers with similar productivity-relevant characteristics, and workers who are simply co-located, are also more likely to be friends. This raises a central identification challenge: the *reflection problem* (Manski, 1993). A correlation between a worker's performance and that of her friends can arise because productive workers select one another as friends, because connected workers experience common shocks, or because own and peer outcomes are simultaneously determined, and disentangling these channels from a genuine effect of network access is generally not possible from correlations alone.

We make progress on this challenge by exploiting the production process in sweater factories. New styles and processes are introduced across workers at different times, with the timing largely determined by production factors, including when existing production runs finish and when new orders arrive. This staggered roll-out generates variation in whether a worker is socially connected to someone with prior experience when she begins producing a new style or component. We compare workers' learning trajectories when they are socially connected to an experienced worker relative to when relevant experience exists in the workplace but is not connected to them through a social tie. This design allows us to separate access to productive knowledge through the network from general learning-by-doing and common production shocks.

## 3. Within-Garment Learning Curves

We define a garment at the *style-component* level, which distinguishes individual components within a factory style. This is the relevant production unit for our analysis because workers perform operations on specific garment components, and the associated production requirements and learning opportunities can differ across components of the same style. The data contain 17,430 distinct style-components. The median style-component is produced by 25 workers across four production lines, while the median worker–garment spell lasts two observed production days (Table 7). Despite the short median spell, the data provide substantial support for estimating early learning: 118,330 worker–garment spells contribute observations over days 0–7.

The production data allow us to construct three measures of worker output, summarized in

Table 8. The first is *physical output*, measured as the number of pieces produced. Because workers perform operations that differ in their complexity and expected completion time, physical output is not directly comparable across tasks. Each operation is assigned a *standard minute value* (SMV), which measures the standard amount of time required to complete one unit of that operation under normal production conditions. We construct *standard-minute output* by multiplying the number of pieces completed by the operation-specific SMV and summing across operations performed by the worker that day. Standard-minute output therefore places heterogeneous production tasks on a common scale. Finally, we define *efficiency* as standard-minute output divided by recorded work minutes, measuring standardized output per unit of labor input.

We first establish the presence of a within-garment learning margin. Figure 1 plots each production measure against the number of observed production days since a worker first begins producing a style-component. Day zero denotes the worker's first observed production day on that style-component, and subsequent coefficients trace the within-garment learning profile. The matched sample requires nonmissing observations for all three production outcomes and that the worker–garment spell remain observed through the displayed horizon.

Relative to day 0, log efficiency, which adjusts for hours worked, is 0.066 higher on day 1 and 0.119 higher by day 7, corresponding to increases of approximately 7 and 13 percent. Output and standard minutes rise by more over the same period, approximately 29 percent on day 1 and 25 percent by day 7, consistent with part of the immediate output gain reflecting greater time devoted to the new garment. Output and standard minutes attenuate around days 5-7, while estimated efficiency remains elevated. This pattern is consistent with a reduction in time allocated to the garment: relative to day 0, log allocated hours decline from 0.212 on day 3 to 0.100 on day 7. The continued rise in efficiency indicates that production pace improves over the week even as output growth moderates. The peer-exposure estimates in Section 5 therefore operate over an economically meaningful margin of within-garment learning.

## 4. Leaders, Followers, and Early Assignment

New styles and style-components are introduced across workers at different times, with timing largely determined by production factors such as when existing runs finish and new orders arrive. We leverage this staggered rollout to study the importance of social ties in on-the-job learning: comparing workers with different exposure to more experienced coworkers as production ramps up allows us to trace learning curves conditional on network position – though, as we show below, this timing variation is not fully exogenous, motivating the causal approach in Section 6.

A worker who starts a style-component on the first or second day it appears on her assigned line is defined as a *leader*; workers who begin later are *followers*. Leaders account for 40.1 percent of worker–garment assignments, with nearly identical shares among men and women. Moreover, 99.7 percent of workers are observed as a leader at least once, indicating that leadership is an assignment-level role rather than a fixed worker type (Table **??**). For followers, early peer exposure

is determined by which workers have already begun producing the same garment when the follower enters production. Since some of these experienced coworkers are friends and others are not, and may be located on or off the follower's production line, this staggered production process generates substantial variation in the type of experienced peers available when a worker begins a new garment. We use this variation in the next section to examine whether followers' initial performance and subsequent learning differ with their exposure to experienced friends.

## 5. Early Friend Exposure: Entry Performance and Learning

We next examine whether followers perform differently when they are exposed to experienced coworkers who are also their friends. We focus on two margins: performance when a worker first begins producing a garment and subsequent learning over the first several production days.

We define two workers as friends if either nominated the other. This yields 7,369 eligible undirected ties among 4,184 connected workers. Early coworkers are substantially more numerous than early friends: 26.0 percent of worker–garment assignments include at least one early friend (mean 0.403), compared with 95.8 percent with at least one early non-friend (mean 18.586). We therefore distinguish exposure to friends from exposure to other experienced coworkers rather than using a pooled measure of early coworker exposure.

We further decompose early exposure by whether the experienced coworker is on the same production line as the focal worker. This allows us to compare early friends with early non-friends separately within the same-line and off-line coworker pools. Entry performance is measured on the focal worker's first observed production day on the garment, while early learning measures the change in performance over subsequent production days. To account for systematic differences in the workers providing early exposure, all specifications control for mean baseline in-degree among early peers and for their age, productivity, and tenure, entered separately for male and female leaders. When a focal worker has no leader of a given gender present, the corresponding characteristics are imputed as zero and we include an indicator for the presence of at least one leader of that gender. Table 10 reports the full decomposition by friendship status and line location.

An additional early same-line friend predicts 0.023 log points, or approximately 2.3 percent, higher entry performance. This association is significantly larger than that for a same-line non-friend (difference 0.025, $p < 0.001$) and that for an off-line friend (difference 0.017, $p = 0.018$). Thus, higher entry performance is specifically associated with exposure to an experienced friend on the same production line, rather than with exposure to experienced coworkers generally or with friendship elsewhere in the factory.

The pattern differs for subsequent learning. Both same-line (0.024) and off-line (0.016) early friends have larger coefficients than their corresponding non-friend counterparts (differences 0.020 and 0.018, $p < 0.001$ and $p = 0.034$). Unlike for entry performance, however, the coefficients on same-line and off-line friends are statistically indistinguishable ($p = 0.454$). Friendship therefore predicts faster early learning even when the experienced friend is located elsewhere in the factory.

The contrast between entry performance and learning is informative about potential mechanisms. Because friends are compared with non-friends separately within same-line and off-line coworker pools, these contrasts help account descriptively for shocks associated with having more experienced workers available on the focal worker's line or elsewhere in the factory. Physical co-presence with a friend appears particularly important for the association with *where* a worker begins, but less so for *how quickly* performance improves thereafter. The entry-performance pattern is consistent with mechanisms that operate through direct interaction on the production line, such as coordination or immediate assistance. The learning pattern is also consistent with mechanisms that can operate across locations, including the transmission of garment-specific information or advice. Information may, for example, diffuse to workers on other lines with some delay, generating similar learning effects without a corresponding effect on initial performance.

The main pattern is similar when we allow the relationship between early friend exposure and outcomes to vary with focal-worker gender and network centrality (Table 12). The pooled interaction specifications do not provide evidence of a sharp gender difference in these exposure associations.

These results document a systematic relationship between realized exposure to experienced friends and followers' entry performance and subsequent learning. A remaining identification question is whether realized early-peer exposure can be treated as plausibly exogenous. In particular, factories may systematically select which workers begin new garments early, so the composition of experienced coworkers available when a follower enters production may itself be selected.

Table 11 examines this assignment process by relating two measures of early assignment – starting the factory production run early and being a same-line leader – to worker characteristics. Tenure and baseline friend in-degree both predict early assignment, and joint tests of the gender-interaction terms reject equality of the characteristic slopes for men and women ($p = 0.001$ for factory-level early starting and $p < 0.001$ for same-line leader status). The positive association between baseline friend in-degree and early assignment is particularly relevant for our setting: more central workers appear to be disproportionately represented among those who initiate new garment runs and therefore among the experienced peers available to later starters.

Section 6 develops the additional variation and controls required to distinguish the effect of social connection from selective assignment into early-peer exposure.

## 6. Future Directions

### 6.1 Strengthening the Causal Design

Our analysis thus far shows that realized early exposure is generated by an assignment process correlated with worker characteristics, and the feasible set of early peers varies across workers and garments (Table 11). Identification is therefore two-sided. On the exposure side, the design requires a measure of each worker's *expected* early exposure constructed from her feasible assignment set rather than realized exposure; a strictly predetermined productivity control based only on pre-garment

outcomes, since the current measure uses each worker's full observed history; and controls for assignment eligibility, such as garment designation or gauge. On the friendship-formation side, Section 2 identifies co-onboarding timing and line assignment, and their interaction with gender, as candidate sources of plausibly exogenous variation in *who becomes a worker's friend*. Future work aims to address both margins, separating the effect of friendship from the worker characteristics that predict early exposure to friends.

### 6.2 Longer-Run Outcomes, Gender Heterogeneity, & Counterfactuals

We are incorporating data on worker promotions, both within operator ranks and from operator to supervisor – a margin with substantially higher earnings and decision-making authority than the productivity outcomes we study above, and one where persistent gender gaps remain a first-order and largely unresolved concern in manufacturing labor markets. As our design lets us isolate the causal contribution of horizontal network access to worker outcomes, we are well positioned to quantify how much of this gender gap in promotion and earnings is attributable to differential position in, and exposure to, workplace networks. This is a channel that has not been quantified in this literature to our knowledge, and one whose contribution would point directly to concrete policy levers.

We will also use our causal estimates of peer exposure effects to simulate the impact of changes to factory organization. Concretely, we will construct counterfactual assignments that reallocate high-productivity peers more evenly across lines and onboarding cohorts, and use our estimated exposure effects to predict the resulting change in productivity and in the gender gap in advancement under each alternative policy. Because these simulated policies operate through scheduling and staffing decisions that factories already make, rather than requiring new investment, they offer a low-cost complement to the promotion-gap analysis above.

# Tables and Figures

## A. Descriptives Detail

Table 1: Baseline Worker Characteristics and Friendship Nomination Rates

| | | Gender | | | Age | | | Tenure | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | All | Men | Women | p-value | Below Median | Above Median | p-value | Below Median | Above Median | p-value |
| Age (years) | 29.55 | 29.42 | 29.77 | 0.074* | 24.22 | 34.87 | 0.000*** | 28.98 | 30.12 | 0.000*** |
| | (6.30) | (6.33) | (6.25) | | (3.19) | (3.54) | | (6.37) | (6.18) | |
| Tenure (months) | 38.08 | 38.12 | 38.02 | 0.935 | 30.79 | 45.40 | 0.000*** | 15.76 | 60.57 | 0.000*** |
| | (36.19) | (37.74) | (33.32) | | (23.56) | (44.26) | | (10.66) | (38.83) | |
| Share Muslim | 0.98 | 0.99 | 0.98 | 0.392 | 0.98 | 0.98 | 0.815 | 0.99 | 0.98 | 0.001*** |
| | (0.13) | (0.12) | (0.13) | | (0.13) | (0.12) | | (0.10) | (0.15) | |
| Friend out-degree (0–3) | 2.34 | 2.46 | 2.12 | 0.000*** | 2.32 | 2.35 | 0.376 | 2.23 | 2.44 | 0.000*** |
| | (1.08) | (0.99) | (1.19) | | (1.08) | (1.07) | | (1.16) | (0.98) | |
| Friend in-degree | 1.82 | 2.09 | 1.36 | 0.000*** | 1.66 | 1.99 | 0.000*** | 1.36 | 2.28 | 0.000*** |
| | (1.96) | (2.16) | (1.46) | | (1.78) | (2.12) | | (1.49) | (2.25) | |
| Share with zero friends nominated | 0.13 | 0.10 | 0.18 | 0.000*** | 0.13 | 0.12 | 0.474 | 0.16 | 0.09 | 0.000*** |
| | (0.33) | (0.30) | (0.38) | | (0.34) | (0.33) | | (0.37) | (0.29) | |
| Share with zero incoming nominations | 0.28 | 0.24 | 0.35 | 0.000*** | 0.31 | 0.26 | 0.001*** | 0.35 | 0.22 | 0.000*** |
| | (0.45) | (0.43) | (0.48) | | (0.46) | (0.44) | | (0.48) | (0.41) | |
| Sample size | 4593 | 2925 | 1668 | . | 2295 | 2296 | . | 2305 | 2288 | . |

*Notes:* Sample restricted to baseline survey completers. Standard deviations in parentheses. p-values from two-sample t-tests of equality of means across the two groups in each column group. Age split at the sample median (29.6 years); tenure split at the sample median (28.4 months). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Network Size by Gender and Tenure

| | Out-degree | | | In-degree | | |
|---|---|---|---|---|---|---|
| Tenure bin | Men | Women | Difference | Men | Women | Difference |
| < 1 yr | 2.38 | 1.97 | -0.40*** | 1.29 | 0.92 | -0.37*** |
| | (1.06) | (1.25) | | (1.52) | (1.17) | |
| 1 - 3 yrs | 2.52 | 2.21 | -0.31*** | 1.82 | 1.29 | -0.53*** |
| | (0.93) | (1.12) | | (1.80) | (1.41) | |
| 3+ yrs | 2.62 | 2.31 | -0.31*** | 3.40 | 1.88 | -1.52*** |
| | (0.85) | (1.09) | | (2.83) | (1.73) | |

*Notes:* Out-degree is the number of friends named (0–3) among baseline respondents. In-degree is the number of baseline respondents who named the worker. Cells report means; standard deviations are in parentheses below. Difference is Women − Men. Stars report two-sided difference-in-means tests: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Worker-Day Productivity Measures

| Measure | Observations | Mean | SD | P25 | Median | P75 |
|---|---|---|---|---|---|---|
| Physical output (pieces) | 1,524,662 | 102.726 | 233.038 | 24.000 | 48.000 | 118.000 |
| Standard minutes produced | 1,524,662 | 385.474 | 667.256 | 154.680 | 271.830 | 456.300 |
| Recorded work hours | 1,524,662 | 11.380 | 1.988 | 10.033 | 11.250 | 12.767 |
| Efficiency (standard minutes per work minute) | 1,487,186 | 0.642 | 12.425 | 0.225 | 0.409 | 0.684 |

*Notes:* The unit is a worker-day. Physical output is the number of recorded pieces produced. Standard minutes produced equal component-specific standard minutes per piece times output, summed across all styles and components produced by a worker that day. Efficiency is standard minutes produced divided by recorded work minutes (work hours times 60). The regressions use the natural logs of physical output, standard minutes, and efficiency.

Table 3: Homophily by Covariate: Friend Network

| Covariate | Observed (%) | Expected (%) | Excess (pp) |
|---|---|---|---|
| Gender | 83.57 | 53.99 | 29.58 |
| Religion (Muslim) | 97.18 | 96.86 | 0.32 |
| Age bin | 34.46 | 25.94 | 8.52 |
| Tenure bin | 56.67 | 45.02 | 11.65 |
| Floor | 87.00 | 40.93 | 46.07 |

*Notes:* Expected is the same-group tie rate under random mixing within factory×batch, excluding self-nominations. For category $k$, the benchmark contribution is $\frac{n_k}{N}\frac{n_k-1}{N-1}$. Excess equals observed minus expected, in percentage points.

Table 4: Friendship Tie Formation: Co-onboarding, Spatial Placement, and Homophily (Two-Way Clustered SEs)

| | ≤1m | ≤3m | ≤6m | ≤12m |
|---|---|---|---|---|
| Co-onboarded ≤ 1 month | 0.00286*** | | | |
| | (0.000398) | | | |
| Co-onboarded ≤ 3 months | | 0.00143*** | | |
| | | (0.000251) | | |
| Co-onboarded ≤ 6 months | | | 0.000902*** | |
| | | | (0.000199) | |
| Co-onboarded ≤ 12 months | | | | 0.000615*** |
| | | | | (0.000166) |
| Same production line | 0.0704*** | 0.0704*** | 0.0704*** | 0.0704*** |
| | (0.00201) | (0.00201) | (0.00201) | (0.00201) |
| Same section (factory × floor) | 0.00479*** | 0.00480*** | 0.00480*** | 0.00480*** |
| | (0.000301) | (0.000301) | (0.000301) | (0.000301) |
| Same gender | 0.00412*** | 0.00412*** | 0.00412*** | 0.00413*** |
| | (0.000164) | (0.000164) | (0.000164) | (0.000164) |
| Same religion (Muslim) | 0.000566** | 0.000582** | 0.000581** | 0.000590** |
| | (0.000245) | (0.000246) | (0.000246) | (0.000244) |
| Same home district | 0.00389*** | 0.00390*** | 0.00390*** | 0.00390*** |
| | (0.000462) | (0.000462) | (0.000463) | (0.000462) |
| Constant | -0.00264*** | -0.00267*** | -0.00268*** | -0.00271*** |
| | (0.000262) | (0.000265) | (0.000265) | (0.000263) |
| Observations | 1037432 | 1037432 | 1037432 | 1037432 |
| R-squared | 0.048 | 0.048 | 0.048 | 0.048 |
| Mean(outcome) | 0.0064 | 0.0064 | 0.0064 | 0.0064 |

*Notes:* LPM dyadic regressions. Each observation is an undirected worker pair $(i, j)$ within the same factory × batch. Outcome = 1 if either worker nominated the other as a friend. Dyad universe = all $\binom{n}{2}$ pairs within factory × batch. Factory × batch FE throughout. SEs two-way clustered at ego and alter level (Cameron, Gelbach & Miller 2011). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Friendship Tie Formation: 6-Month Co-onboarding Interactions

| | Base | +Line | +Gender | +District | All |
|---|---|---|---|---|---|
| Co-onboarded $\leq$ 6 months | 0.000902*** | 0.000000610 | 0.000244 | 0.000580*** | -0.000940*** |
| | (0.000199) | (0.000117) | (0.000204) | (0.000192) | (0.000220) |
| Co-onboarded × Same line | | 0.0239*** | | | 0.0238*** |
| | | (0.00433) | | | (0.00433) |
| Co-onboarded × Same gender | | | 0.00117*** | | 0.00116*** |
| | | | (0.000368) | | (0.000370) |
| Co-onboarded × Same home district | | | | 0.00611*** | 0.00564*** |
| | | | | (0.00137) | (0.00133) |
| Same production line | 0.0704*** | 0.0648*** | 0.0704*** | 0.0704*** | 0.0649*** |
| | (0.00201) | (0.00222) | (0.00201) | (0.00201) | (0.00222) |
| Same section (factory × floor) | 0.00480*** | 0.00484*** | 0.00480*** | 0.00480*** | 0.00484*** |
| | (0.000301) | (0.000302) | (0.000301) | (0.000301) | (0.000302) |
| Same gender | 0.00412*** | 0.00413*** | 0.00389*** | 0.00412*** | 0.00390*** |
| | (0.000164) | (0.000164) | (0.000173) | (0.000164) | (0.000172) |
| Same religion (Muslim) | 0.000581** | 0.000589** | 0.000587** | 0.000576** | 0.000590** |
| | (0.000246) | (0.000244) | (0.000245) | (0.000246) | (0.000244) |
| Same home district | 0.00390*** | 0.00389*** | 0.00390*** | 0.00267*** | 0.00275*** |
| | (0.000463) | (0.000461) | (0.000463) | (0.000468) | (0.000468) |
| Observations | 1037432 | 1037432 | 1037432 | 1037432 | 1037432 |
| R-squared | 0.048 | 0.049 | 0.048 | 0.048 | 0.049 |
| Mean(outcome) | 0.0064 | 0.0064 | 0.0064 | 0.0064 | 0.0064 |

*Notes:* LPM dyadic regressions. Outcome = 1 if either worker nominated the other. Each observation is an undirected worker pair within factory × batch. All columns include the full set of main effects. Columns 2–4 add one interaction at a time; column 5 includes all three jointly. Factory × batch FE throughout. SEs two-way clustered at ego and alter level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6: Raw Peer-Productivity and Exit Correlations: Same-Line and Off-Line Friends and Non-Friends

| | Own Efficiency (std.) (1) | Exited (2) |
|---|---|---|
| Own resid. efficiency (std) | | -0.001** |
| | | (0.000) |
| Female × own resid. efficiency | | 0.001 |
| | | (0.002) |
| Avg. off-line friend eff. (std) | 0.063* | -0.000 |
| | (0.035) | (0.000) |
| Female × off-line friend eff. | 0.070 | -0.005 |
| | (0.110) | (0.007) |
| Avg. same-line friend eff. (std) | 0.243*** | -0.001*** |
| | (0.068) | (0.000) |
| Female × same-line friend eff. | 0.377*** | -0.001 |
| | (0.043) | (0.003) |
| Avg. off-line NON-friend eff. (std) | 0.378*** | 0.002** |
| | (0.036) | (0.001) |
| Female × off-line NON-friend eff. | -0.258*** | -0.003*** |
| | (0.040) | (0.001) |
| Avg. same-line NON-friend eff. (std) | -0.068 | -0.001* |
| | (0.045) | (0.001) |
| Female × same-line NON-friend eff. | 0.050 | 0.001 |
| | (0.034) | (0.000) |
| Has ≥1 off-line friend | 0.003 | -0.006 |
| | (0.003) | (0.012) |
| Has ≥1 same-line friend | -0.006 | -0.016 |
| | (0.006) | (0.013) |
| Avg. friend baseline skill (std) | -0.001 | -0.012** |
| | (0.002) | (0.005) |
| Own baseline skill (std) | 0.002 | 0.008 |
| | (0.002) | (0.008) |
| Female | -0.017* | 0.028 |
| | (0.009) | (0.020) |
| Age | 0.001 | -0.002 |
| | (0.000) | (0.001) |
| Tenure (months) | 0.000 | -0.001 |
| | (0.000) | (0.000) |
| Avg. friend tenure (std) | -0.001 | 0.003 |
| | (0.003) | (0.012) |
| Avg. friend age (std) | 0.005 | 0.005 |
| | (0.003) | (0.011) |
| Share women among friends (std) | 0.003 | -0.007 |
| | (0.003) | (0.010) |
| Observations | 346397 | 346397 |
| $R^2$ | 0.144 | 0.146 |

*Notes:* Sample is a worker-day panel of production days. Column (1) regresses a worker's own daily efficiency (residualized and standardized) on the contemporaneous average residualized efficiency of her same-line and off-line friends and non-friends (each standardized), interacted with a Female indicator; column (2) replaces the outcome with an indicator for exit and additionally controls for the worker's own residualized efficiency (interacted with Female). Both columns residualize on factory, line, day, and factory×line fixed effects and control for own and average friend baseline skill, age, and tenure, the share of women among friends, and indicators for having at least one same-line and one off-line friend. SEs clustered by skills cluster. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table 7: Support for Style and Style-Component Garment Definitions

| | Style | Style-component |
|---|---|---|
| Garments | 6,068 | 17,430 |
| Median workers per garment | 76 | 25 |
| Median lines per garment | 7 | 4 |
| Median floors per garment | 1 | 1 |
| Median component groups per garment | 1 | 1 |
| Garments with at least 2 workers | 5,971 | 16,469 |
| Garments with at least 5 workers | 5,757 | 14,851 |
| Median observed days per worker–garment spell | 2 | 2 |
| Spells supporting days 0–7 | 93,634 | 118,330 |
| Spells supporting days 0–20 | 17,073 | 23,023 |

*Notes:* A garment is defined within factory. Worker–garment duration is calculated only for observed worker–garment pairs; workers not observed producing a given garment are not included as zero-day spells. Days are distinct observed production days, not calendar days. Lines and floors use the time-invariant roster assignments.

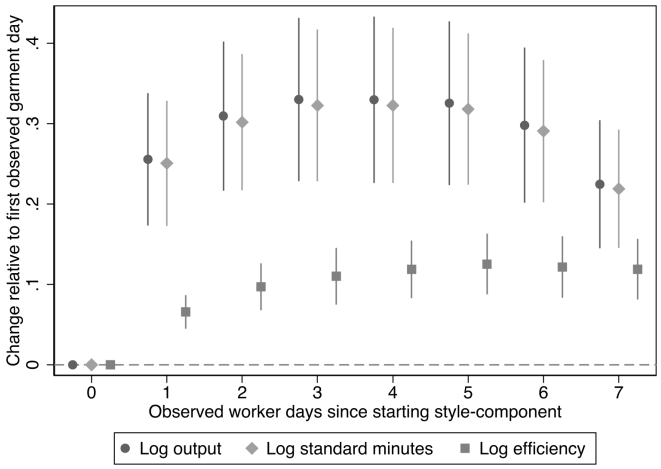
Table 9: Leader and Follower Composition by Focal-Worker Gender

| | All | Male | Female |
|---|---|---|---|
| *Worker–garment assignments* | | | |
| Leaders | 343,754 | 229,922 | 113,832 |
| Followers | 513,221 | 342,048 | 171,173 |
| Leader share (%) | 40.1 | 40.2 | 39.9 |
| Mean within-garment leader share (%) | 59.0 | 58.0 | 54.4 |
| *Worker-level cross section* | | | |
| Workers | 6,615 | 4,480 | 2,135 |
| Workers ever observed as leaders | 6,593 | 4,467 | 2,126 |
| Ever-leader share (%) | 99.7 | 99.7 | 99.6 |

*Notes:* The sample contains observed worker–style-component assignments with nonmissing gender and assigned-line entry timing; it does not condition on survival to a learning-curve horizon. A leader begins the style-component on its first observed day in the worker's assigned line. Assignment counts treat each worker–style-component pair once. The mean within-garment share first calculates the leader fraction within each factory–style-component and then weights garments equally. Gender-specific within-garment shares are calculated among workers of that gender in garments where that gender is observed. The ever-leader share is the fraction of distinct workers observed as a leader on at least one style-component.

## B. Learning Curves and Early Assignment

Figure 1: Matched-Sample Learning Curve Through Day 7




*Notes:* Coefficients on indicators for observed days since the worker started the style-component, day 0 omitted. Regressions absorb worker-by-style-component and calendar-date fixed effects; SEs clustered by skills cluster.

Table 10: Early-Friend Exposure, Entry Performance, and Early Learning: Friend × Line Decomposition

| | (1)<br>Entry performance: day 0 | (2)<br>Learning: days 1–3 minus day 0 |
|---|---|---|
| Early friends: same line | 0.024*** | 0.017*** |
| | (0.004) | (0.005) |
| Early friends: off line | 0.007 | 0.015* |
| | (0.006) | (0.008) |
| Early non-friends: same line | -0.003 | -0.001 |
| | (0.003) | (0.003) |
| Early non-friends: off line | 0.000 | -0.001 |
| | (0.000) | (0.001) |
| Friend minus non-friend: same line | 0.026 | 0.018 |
| P-value: friend equals non-friend, same line | 0.000 | 0.000 |
| Friend minus non-friend: off line | 0.007 | 0.016 |
| P-value: friend equals non-friend, off line | 0.210 | 0.052 |
| Same-line friend minus off-line non-friend | 0.023 | 0.018 |
| P-value: same-line friend equals off-line non-friend | 0.000 | 0.002 |
| Off-line friend minus same-line non-friend | 0.010 | 0.016 |
| P-value: off-line friend equals same-line non-friend | 0.178 | 0.105 |
| Same line minus off line: friends | 0.016 | 0.002 |
| P-value: same line equals off line, friends | 0.024 | 0.833 |
| Gender-specific early-leader composition controls | Yes | Yes |
| Workers | 4361 | 4361 |
| Garments | 14755 | 11861 |
| Worker–garment observations | 490350 | 299827 |
| Mean dependent variable | 4.493 | 0.030 |

*Notes:* Reports the fully decomposed friend-status-by-line specification for each outcome. Entry performance is log standard minutes on the focal worker's first observed garment day; learning is mean log standard minutes on observed days 1–3 minus day 0. Both columns absorb worker and garment fixed effects, control for mean in-degree in each early-peer friend-status-by-line cell, and control separately for the age, tenure, and long-run productivity composition of early women and men in same-line and off-line pools. When a gender-specific leader pool is absent, its means are imputed as zero and a presence indicator is included. The contrast rows compare each friend slope with early non-friends on the same line and off line, helping account descriptively for shocks associated with more early leaders in each location. Standard errors are clustered by skills cluster. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Table 11: Worker Characteristics, Long-Run Productivity, and Early Garment Assignment

| | Factory early starter | | Assigned-line leader | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Pooled | Gender interactions | Pooled | Gender interactions |
| Female | 0.0003 | 0.0022 | 0.0043 | 0.0071 |
| | (0.0045) | (0.0042) | (0.0091) | (0.0087) |
| Age (years) | 0.0005 | 0.0009** | 0.0006 | 0.0012* |
| | (0.0004) | (0.0003) | (0.0006) | (0.0006) |
| Tenure (months) | 0.0548** | 0.0436** | 0.0666 | 0.0471 |
| | (0.0207) | (0.0207) | (0.0490) | (0.0431) |
| Baseline friend in-degree | 0.0023*** | 0.0014** | 0.0035*** | 0.0022 |
| | (0.0006) | (0.0007) | (0.0011) | (0.0014) |
| Estimated long-run worker productivity | 0.0001 | -0.0000 | 0.0001 | -0.0001 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Female × age | | -0.0012*** | | -0.0017** |
| | | (0.0003) | | (0.0006) |
| Female × tenure | | 0.0362 | | 0.0638 |
| | | (0.0219) | | (0.0472) |
| Female × friend in-degree | | 0.0041** | | 0.0062 |
| | | (0.0018) | | (0.0036) |
| Female × worker productivity | | 0.0011* | | 0.0027*** |
| | | (0.0006) | | (0.0006) |
| Early-start definition | Factory day 0–1 | Factory day 0–1 | First line day | First line day |
| Assignment fixed effects | Garment | Garment | Garment × line | Garment × line |
| Gender interactions | No | Yes | No | Yes |
| P-value: interactions jointly zero | . | 0.001 | . | 0.000 |
| P-value: male slopes jointly zero | . | 0.002 | . | 0.046 |
| P-value: female slopes jointly zero | . | 0.002 | . | 0.000 |
| Wild-bootstrap p-value: worker productivity | 0.504 | 0.910 | 0.505 | 0.879 |
| Wild-bootstrap p-value: female × worker productivity | | 0.184 | | 0.296 |
| Worker–garment assignments | 589584 | 589584 | 571134 | 571134 |

*Notes:* The unit is a worker–style-component assignment in the baseline-network sample. Columns 1–2 equal one when the worker starts on factory production day 0 or 1 and compare workers assigned to the same factory-specific style-component. Columns 3–4 equal one when the worker starts on the first day that the garment appears on the worker's assigned line and compare workers within the same garment–line cell. All continuous characteristics are centered at their balance-sample means. In the interaction columns, uninteracted slopes apply to male workers and interaction coefficients are female–male differences. Estimated worker productivity is the worker fixed effect from a daily efficiency regression absorbing factory-line and calendar-date fixed effects. Because it uses the worker's full observed production history, it is a descriptive long-run productivity control rather than a strictly predetermined measure. The two wild-bootstrap rows report 999-rep skills-cluster bootstrap p-values for the coefficients involving this generated productivity control; the second is applicable only to gender-interaction specifications. Friendship in-degree is measured in the directed baseline nomination network and set to zero for baseline respondents with no nominations received. Standard errors clustered by skills cluster are in parentheses. This is an observed-balance diagnostic, not by itself proof of random assignment. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

## C. Gender Heterogeneity Detail

Table 12: Early-Friend Exposure by Focal Gender, Peer Gender, and Line Location

| | (1) Entry performance: day 0 | (2) Learning: days 1–3 minus day 0 |
|---|---|---|
| Male focal: women friends, same line | 0.011 | 0.038*** |
| | (0.008) | (0.008) |
| Male focal: men friends, same line | 0.025*** | 0.023*** |
| | (0.006) | (0.006) |
| Male focal: women friends, off line | 0.001 | 0.006 |
| | (0.021) | (0.025) |
| Male focal: men friends, off line | 0.001 | 0.018** |
| | (0.007) | (0.008) |
| Female − male: women friends, same line | 0.016** | -0.004 |
| | (0.007) | (0.010) |
| Female − male: men friends, same line | -0.013** | -0.003 |
| | (0.006) | (0.009) |
| Female − male: women friends, off line | 0.023 | 0.003 |
| | (0.022) | (0.031) |
| Female − male: men friends, off line | 0.004 | 0.019 |
| | (0.013) | (0.018) |
| Female slope women friends same line | 0.027 | 0.033 |
| P-value female slope women friends same line | 0.002 | 0.002 |
| Female slope men friends same line | 0.012 | 0.020 |
| P-value female slope men friends same line | 0.125 | 0.072 |
| Female slope women friends off line | 0.024 | 0.009 |
| P-value female slope women friends off line | 0.041 | 0.621 |
| Female slope men friends off line | 0.004 | 0.037 |
| P-value female slope men friends off line | 0.738 | 0.064 |
| Worker FE | Yes | Yes |
| Garment FE | Yes | Yes |
| Workers | 4361 | 4361 |
| Garments | 14755 | 11861 |
| Worker–garment observations | 490350 | 299827 |
| Mean dependent variable | 4.493 | 0.030 |
| Sample | Baseline network | Baseline network |

*Notes:* Each outcome is estimated in one pooled regression. Rows jointly distinguish the early friend's gender and line location and interact every exposure with focal-worker gender. Uninteracted coefficients are male-focal slopes; interactions are female-minus-male differences. The bottom panel reports implied female slopes and their two-sided p-values. Entry performance is log standard minutes on the focal worker's first observed garment day. Learning is mean log standard minutes on observed days 1–3 minus day 0 and requires at least two observed worker–garment days. Regressions control for mean in-degree in each early-peer friend-status by line-location cell; focal-worker in-degree is absorbed by worker fixed effects. Garment fixed effects are included and standard errors are clustered by skills cluster. The estimates are descriptive until expected exposure and the assignment mechanism are incorporated. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

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