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CEO GENDER BIAS IN THE FORMATION OF FIRM-TO-FIRM TRANSACTIONS

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ABSTRACT

This study examines an unexplored channel of female CEO disadvantage: CEO gender bias in forming business networks. Using supplier-buyer linkage data from Japanese firms, we find that CEOs of the same gender are more likely to trade than those of the opposite gender, particularly in small and medium-sized rms. As most CEOs are male, this same-gender bias restricts the trading opportunities for female CEOs compared with their male counterparts. Our CEO survey revealed frictions that hinder cross-gender encounters, suggesting that creating venues to promote female-male CEO interactions could effectively achieve gender equity through expanding the business networks of female CEOs.

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1 Introduction

Despite government efforts to promote gender equity in the labor market, women are still underrepresented in top career positions. For example, recent U.S. data show that only approximately 21% of all firms are female-led (Census Bureau, 2023).[1] The situation in Japan—our setting—is dire, with female CEOs representing, at best, approximately 14% of all firms.[2] Furthermore, female-led firms do not perform as well as male-led firms in sales, growth, and size (Fairlie and Robb, 2009). Because CEOs have a significant influence on firm performance (e.g., Bertrand and Schoar, 2003; Bloom and Van Reenen, 2007; Bandiera et al., 2020) and female employment (Chiplunkar and Goldberg, 2024), understanding the barriers that female CEOs encounter in the business environment is crucial not only for promoting equity but also for economic efficiency (Hsieh et al., 2019; Chiplunkar and Goldberg, 2024).

This study investigates an unexplored channel of female CEO disadvantage in business operations: gender bias in the formation of firm-to-firm transactions.[3] While recent literature highlights the importance of business networks for firm performance (Cai and Szeidl, 2018; Asiedu et al., 2023), little is known about how such networks are formed, particularly in terms of CEO gender. Sociological literature has suggested that individuals with similar characteristics (e.g., gender, race, education, and income) tend to establish relationships, from friendships to marriages, known as "homophily" (e.g., Currarini et al., 2009; Eika et al., 2019; Chetty et al., 2022).

We hypothesize that this tendency, particularly with respect to gender, extends beyond individual relationships to inter-firm interactions, as the personal networks of CEOs may lead to the establishment of firm-level transactions. As most CEOs are male, such gender homophily in transaction networks—if it exists—may reduce the trading opportunities for female CEOs relative to male CEOs, leading to smaller business networks of female CEOs. Indeed, a simple correlational analysis of our data on supplier-buyer linkages reveals that female CEOs have smaller networks in terms of the number of suppliers and buyers compared with male CEOs (Figure 1). In addition, Figure 2 demonstrates a positive relationship between network size and firm performance (measured by log sales per employee or credit score of the firms) for both CEO genders. Taken together, female CEOs' disadvantage in building business networks can be a potential determinant of

[1] Source: https://www.census.gov/library/visualizations/2023/comm/women-owned-employer-businesses.html (accessed August 15, 2023)

[2] Authors' calculations from TSR data.

[3] The literature suggests various impediments to the business operations for female CEOs, including childcare responsibilities (Delecourt and Fitzpatrick, 2021), lack of access to financing (Ewens and Townsend, 2020), and lack of business experience (Fairlie and Robb, 2009).

their lower firm performance.

Our study leverages unique annual frequency panel data on approximately 1 million Japanese firms, which cover approximately 70% of all Japanese firms from 2008 to 2020. The data are obtained from a major credit reporting company in Japan, Tokyo Shoko Research, LTD. (henceforth, TSR). Two important features of the TSR data make it an ideal dataset for our study. First, the data contains detailed information on supplier-buyer relationships. TSR data include as many as 38.8 million supplier-buyer links over the period 2008–2020, with roughly 3 million links per year. Second, the data report detailed information on CEO characteristics, including gender. Importantly, the data include other key CEO attributes such as age, education, and birth prefecture, allowing us to control for other important homophily variables that may be well correlated with CEO gender. To our knowledge, this is the only dataset that simultaneously includes details on transaction networks *and* rich characteristics of CEOs.

We document the presence of CEO gender homophily in firm-to-firm transactions: Transactions are more likely to occur between firms whose CEOs are of the same gender than between firms whose CEOs are of the opposite gender. We present the evidence using two approaches. In the first approach, we consider the firm (either supplier or buyer) as the unit of analysis and compute the share of transactions with female-led firms.[4] We graphically show that the share of transactions with female-led buyers is almost always greater for female-led suppliers than for male-led suppliers *within* the markets in which the set of potential female-led buyers is identical for both female-led and male-led suppliers. This so-called *relative* homophily (e.g., Zeltzer, 2020) indicates the same-gender bias of CEOs in the formation of firm-to-firm transactions.

In the second approach, we utilize the supplier-buyer dyad as the unit of analysis and quantify the precise impact of CEO gender homophily on the probability of transactions. Notably, we apply the latest econometric technique in network data, controlling for supplier and buyer fixed effects (FEs) in a nonlinear difference-in-differences approach using network data (Graham, 2017; Charbonneau, 2017; Jochmans, 2018). Consistent with the firm-level analysis, we find that the trading probabilities of firms led by CEOs of the same gender are 4.7% higher than those of firms led by CEOs of the opposite gender.

An obvious concern is that such same-gender bias we document may also capture the effect of other homophilic factors that are correlated with gender. For instance, as female CEOs tend to have lower levels of education than male CEOs, our gender homophily may

[4]We use "female-CEO firms/suppliers/buyers" and "female-led firms/suppliers/buyers", interchangeably, similar with "male-CEO firms" and "male-led firms".

simply reflect education homophily. The rich information on CEO characteristics in the TSR data enables us to control for other homophily variables, such as CEO education (i.e., both CEOs are from the same school), birthplace (i.e., both CEOs are from the same prefecture), and age (i.e., both CEOs are similar age). Reassuringly, the estimate of gender homophily remains robust even after controlling for these homophily variables.

To further strengthen our findings, we conduct a series of additional analyses. First, we conduct heterogeneity analysis by firm size. If the observed homophily arises through CEO-level social networks or decision-making preferences, the effect should be stronger in smaller firms, wherein CEOs are more actively involved in the transaction formation process. We show that the effect of gender homophily is indeed concentrated among small and medium-sized enterprises (hereafter, SMEs). In particular, CEOs of small firms are 10.9% more likely to form transactions with a CEO of the same gender than with one of the opposite gender, reinforcing the interpretation that CEO involvement is a key factor. Furthermore, we show that firms are more likely to trade when CEOs share hobbies (e.g., golf), which are potential network tools, but only if both are the same gender. If two CEOs of different genders share hobbies, the trading likelihood does not increase. While suggestive, these results also align with our argument that CEOs' personal interactions play an important role in firm-to-firm transactions.

Second, we conduct a robustness check to increase the likelihood that firms in the same market trade similar goods. We redefine markets using finer classifications of three- and four-digit industry codes for both suppliers and buyers, unlike in our main analysis in which we define markets by two-digit industry pairs. Male and female CEOs may operate in systematically different sectors or trade distinct products, and thus, the observed homophily could be a byproduct of market segmentation. We find that the estimated coefficient on gender homophily remains virtually unchanged, suggesting that our results are not driven by differences in product markets.

Third, we conduct a duration analysis to address the possibility that transactions between same-gender CEOs may last longer than those between opposite-gender CEOs, leading to overrepresentation in the data. We examine whether the length of a transaction differs by the gender pairing of CEOs, conditional on a transaction being formed. The results show no statistically significant difference in transaction duration between same-gender and opposite-gender CEO pairs. This supports our main claim that CEO gender homophily is primarily a phenomenon of initiating rather than persisting transactions.

Our final part of the paper examines the underlying mechanisms of CEO gender homophily to shed light on the type of policies that can effectively eliminate it. While

the analysis of supplier-buyer relationship data provides solid evidence of CEO gender homophily in firm-to-firm transactions, it does not address the underlying mechanisms. In particular, it is crucial to discern whether the relatively low likelihood of transactions between opposite-gender CEOs is primarily driven by a scarcity of opportunities to become acquainted with CEOs of the opposite gender in the market (homophily in "meetings") or resistance to engage in trade with opposite-gender CEO firms, even when meetings occur (homophily in "preferences").

Distinguishing between these two mechanisms is important because they have very different policy implications. If homophily reflects frictions that limit cross-gender encounters, such as gendered networks or implicit norms, the policy implications are clearer; targeted interventions to reduce these frictions will be effective. By contrast, if homophily arises from preferences, whether due to ease of communication or discriminatory bias, the appropriate policy response is less obvious and the welfare implications are more ambiguous.

To this end, we conduct our original CEO survey in collaboration with the Cabinet Office of the Government of Japan. We distributed the survey in February 2023 to 25,000 CEOs (12,500 male and 12,500 female) with a 25.7% response rate (N=6,437). Our findings suggest that both homophily in "meetings" and "preferences" are crucial in the formation of transaction networks. For "meetings," female respondents had a 19.9% probability of becoming acquainted with a female CEO, whereas male respondents had only 5.2%—less than a third of the female probability.[5] Given that female CEOs make up 14.4% of the total, female respondents were more likely to meet female CEOs than expected by random chance (19.9% $>$ 14.4%), whereas male respondents were less likely (5.2% $<$ 14.4%). For "preferences," male respondents preferred interacting with male CEOs, whereas female respondents were relatively neutral. However, gender homophily in "preferences" accounted for only a small part of the gender homophily in "meetings," suggesting underlying frictions that limit opposite-gender interactions beyond mere preference.

Our findings have important policy implications. In a market with predominantly male CEOs, the presence of same-gender bias in firm-to-firm transactions disproportionately limits the trading opportunities for female CEOs. Increasing the representation of female CEOs, including through affirmative action, may partially offset this imbalance. However, because gender homophily persists, such interventions could unintentionally reduce opportunities for male CEOs, resulting in efficiency trade-offs. In the final section,

[5]We use the term "respondents" to refer to the CEOs who answered the survey to distinguish from "CEOs", as generally mentioned in the questionnaire.

we formally explore this possibility through counterfactual simulations. These results highlight the importance of directly targeting the mechanisms behind gender homophily rather than simply increasing the representation of female CEOs. As our survey evidence points to frictions that hinder cross-gender interactions among CEOs, policies designed to reduce these frictions, such as inclusive networking events, cross-gender mentorship programs, or structured business-matching platforms, may be more effective in achieving gender equity in inter-firm transactions without reducing overall deal volume.

Related literature.—This paper is related to several strands of literature. First, it is well documented that CEOs significantly influence management practices and firm outcomes (e.g., Bertrand and Schoar, 2003; Bloom and Van Reenen, 2007; Bandiera et al., 2020). In particular, the literature on the consequences of having female executives in firms is mounting. For instance, female executives have been shown to increase female employment (Chiplunkar and Goldberg, 2024), reduce gender promotion gaps at lower ranks (Kunze and Miller, 2017; Cullen and Perez-Truglia, 2023), reduce gender wage gaps at the top of the wage distribution and improve firm performance in firms with higher proportions of female employees (Flabbi et al., 2019), mitigate the unfair punishment of women (Egan et al., 2022), and reduce turnover among women due to harassment incidents (Adams-Prassl et al., 2024).[6] Our study contributes to the literature by examining the impact of CEO gender on interfirm relationships, which are closely tied to firm performance.

Second, our study contributes to the literature on cultural bias in economic relationship formation (e.g., Guiso et al., 2009; Fisman et al., 2017), particularly the recently growing literature on gender bias ("homophily"). Gender homophily has been documented in various contexts, such as students' choices of mentors (Gallen and Wasserman, 2023), patients' choice of doctors (Cabral and Dillender, 2024), doctors' referrals to specialists (Zeltzer, 2020), co-author choice among economists (Davies, 2022; Ductor and Prummer, 2024), and investors' lending decisions to entrepreneurs (Ewens and Townsend, 2020). Gender homophily has been observed in firms, such as in employee referrals in hiring (Beaman et al., 2018) and promotion decisions (Kunze and Miller, 2017; Cullen and Perez-Truglia, 2023). The context of our study is arguably more general as firm-to-firm transactions occur in any business setting across the globe, and our data include transactions from an entire country.

Finally, our study relates to the growing literature on business networks and firm performance (Cai and Szeidl, 2018; Asiedu et al., 2023). Ashraf et al. (2023) show that

[6] Another strand of the literature is the effect of having female board members (e.g., Matsa and Miller, 2011; Ahern and Dittmar, 2012; Matsa and Miller, 2013; Bertrand et al., 2019; Maida and Weber, 2022).

in weak institutional environments such as Zambia, women avoid transacting with men due to expropriation risks, resulting in gender-based market segregation. By contrast, we show that in institutionally strong settings like Japan, women's limited access to business networks stems from different mechanisms. Our CEO survey suggests that male CEOs exhibit a stronger preference for same-gender interactions than female CEOs and points to structural frictions in cross-gender meetings—instead of distrust or contract failures—as an important channel through which women's access to business networks may be limited.

The remainder of the paper is organized as follows. Section 2 describes the data, Section 3 presents the analytical framework and the main findings of this study, and Section 4 reports the results of the survey. Section 5 presents a simple counterfactual simulation to complement the policy discussion and concludes the paper.

2 Data

The TSR data are an annual-frequency panel of approximately 1 million Japanese firms, covering approximately 70% of all Japanese firms from 2008 to 2020.[7] In addition to the basic firm-level characteristics such as employment, sales, credit score, and geographic location, two features of the TSR data make this dataset ideal for our study.

First, the data contain detailed information on the supplier-buyer relationships. TSR's field surveyors request each firm to report up to 24 main suppliers and buyers each year. We note that censoring is not practically binding as less than 0.1% of firms report 24 suppliers and buyers (see Appendix Figure A1). To deal with potential unreported partners, we construct a firm's transaction network by exploiting reverse reporting.[8] There are 38.8 million supplier-buyer links from 2008 to 2020, with an average of approximately 3 million links per year. Second, the data report detailed information about the characteristics of the CEOs, including gender, name, age, education, and birth prefecture, among others.[9] Importantly, while many datasets either contain detailed supplier-buyer transaction networks or detailed CEO characteristics, to the best of our knowledge, the TSR dataset is the only dataset that provides *both* on a large scale. This unique feature enables us to examine the existence of CEO gender homophily in

[7] This dataset is also used in previous studies, including Bernard et al. (2019), Carvalho et al. (2021), and Miyauchi (2024).

[8] Specifically, we consider firm A to be a supplier of firm B if either (i) A reports B as a buyer or (ii) B reports A as a supplier. Previous studies using the TSR data also construct the transaction network in this way (Bernard et al., 2019; Carvalho et al., 2021; Miyauchi, 2024).

[9] A prefecture is a first-level administrative division in Japan, similar to a state or province, of which there are 47 across the country.

firm-to-firm transactions, controlling for the homophily in other CEO characteristics. Notably, we exclude supplier-buyer links between firms with the same CEO, identified by the name of the CEOs. Including transactions between firms with the same CEO could mechanically create an upward bias in the estimate of gender homophily.

However, our data present two significant limitations. First, no price, volume, or commodity information is included. This precludes us from examining the intensive margins of the firm-to-firm transactions. Second, the linkage data do not include firms not surveyed in the TSR data nor final consumers, implying that a firm does not have any transaction partners if all of its partners are outside of the TSR data or if its partners are final consumers. This implies that we exclusively focus on business-to-business (B-to-B) transactions and exclude business-to-consumer (B-to-C) transactions.

2.1 Descriptive statistics

Table 1 presents the summary statistics of the selected characteristics for firms (Panel A) and CEOs (Panel B) separately by the CEO gender. The sample is limited to firms that had no missing values for CEO gender, sales, number of employees, firm age, and credit score. Here, we pool all data across years 2008-2020. Consistent with the previous literature, Panel A shows that female-led firms (Column 1) lag behind male-led firms (Column 2) in sales, firm size (measured by the number of full-time employees), firm age, a fraction of firms listed, and credit scores. Notably, female-led firms have fewer trading partners for both suppliers and buyers than male-led firms. The average number of suppliers (buyers) for female-led firms is 2.5 (2.4), whereas that for male-led firms is 4.6 (4.6), and the differences between female- and male-led firms are statistically significant at the 1% level, as shown in Column (3). Moreover, recall that Figure 1 shows that the cumulative distribution function in the number of suppliers and buyers for female-led firms is first-order stochastically dominated by that of male-led firms. Panel B of Table 1 reports that female CEOs are, on average, older than male CEOs.[10] In addition,female CEOs are less educated than male CEOs, a pattern that aligns with the educational differences observed in the general Japanese population.

In this study, we focus on the quantity (or number) of business links, rather than on the "quality" of the links. Although female CEOs have smaller business networks, the quality of their networks may be higher than that of male CEOs because they are

[10]This may reflect that women have a longer life expectancy than men and often take over businesses after the death of their male spouses in Japan. Indeed, in our survey, we find that paths to becoming CEOs differ by gender, as shown in Appendix Figure A6. Notably, female CEOs exhibit a greater tendency to inherit the position from a previous CEO within their family compared to their male counterparts.

more conscientious in choosing business partners. To examine this possibility, we investigate the difference in the characteristics of firms that are "connected" with female- and male-led firms. Table 2 presents the summary statistics of *buyers* by the gender of CEO *suppliers* to examine this possibility.[11] Owing to the large sample size, most of the differences in the buyer characteristics between female- and male-led suppliers are statistically significant, but the magnitude of the differences is mostly negligible, as shown in Column (3)—the percentage change from the mean of male-led suppliers (except for a few variables that take the log difference). In particular, the log(sales/employee), which can be viewed as a proxy for productivity, is similar, and the difference is not statistically significant at the conventional level despite the large sample size. One obvious exception is log(distance), in which the buyers are 18% closer, on average, for female-led suppliers than for male-led suppliers. This may reflect the type of industry that female-led suppliers enter (e.g., service industry) or the lower mobility of female-led suppliers due to household chores (e.g., Le Barbanchon et al., 2021). Another clear difference is the fraction of female CEO buyers (the last row of the table), with 3.8% for female-led suppliers and only 2.8% for male-led suppliers.

Overall, while this is at best suggestive, the difference in the quality of business ties between male- and female-led firms does not seem large, at least by the observable characteristics in our data.

As CEO gender is rarely observed in transaction data, providing more descriptive statistics of firms by CEO gender is useful. Appendix Table A2 shows the distribution of female- and male-led firms across the industry at a one-digit level. Interestingly, the composition of the industry does not markedly differ across female and male CEOs. The three leading industries are construction, wholesale and retail trade, and manufacturing for both genders. The small differences in industry composition between female- and male-led firms provide rough evidence that concerns about women and men entering different industries or selling different types of goods are not central to understanding the gender homophily we document later.[12]

[11] Conversely, Appendix Table A1 presents the summary statistics of *suppliers* by the gender of CEO *buyers*. We do not find much difference in the quality of business by CEO gender either.

[12] We revisit this issue more formally in Section 3.5.3.

3 Empirical analysis

3.1 Preliminary evidence

Before presenting the analysis, we provide two preliminary pieces of evidence consistent with CEO gender homophily. Table 3 Panel (a) exhibits gender homophily from the supplier's perspective. Female-led suppliers trade 3.9% with female-led buyers, compared with male-led suppliers, who trade 3.0% with female-led buyers. While the difference of 0.9 percentage points may appear small, it is large given that only 6.0% of buyers are female CEOs. Notably, this number (6.0%) is smaller than the overall share of female CEOs (14.4%) in the entire market, since as discussed earlier, we exclusively focus on B-to-B transactions.[13]

Similarly, Table 3 Panel (b) presents the buyer's perspective, indicating parallel evidence of gender homophily. Female (male)-led buyers trade 3.7 (2.8)% with female-led suppliers. The difference of 0.9 percentage points is large given that only 5.4% of suppliers are female CEOs. In sum, from both perspectives, female-led firms are *relatively* more likely to trade with female-led firms than with male-led firms, whereas male-led firms are relatively more likely to trade with male-led firms than with female-led firms.

Figure 3 presents additional evidence of gender homophily by illustrating the share of female-led buyers over the total number of buyers, separately for female- and male-led suppliers. Holding the number of buyers constant to account for a larger network size of male-led suppliers than female-led suppliers, the share of female-led buyers among total buyers is *uniformly* larger for female-led suppliers than for male-led suppliers. Next, we provide more formal evidence of CEO gender homophily.

3.2 Analytical framework

To organize our analysis, we begin by explaining the analytical framework for our study. To address the possibility that the preliminary evidence reflects differences in the industry composition of female- and male-led firms, whereby female CEOs may operate in separate markets with distinct pools of potential trading partners, we then define markets to rigorously demonstrate gender homophily within the same market.

Let K be the set of market segments defined by two-digit ($\approx$100) industry pairs of

[13] Appendix Table A3 shows the fraction of female CEOs, overall and by firm size. The table shows that female CEOs represent 5.7% of all firms, whereas 94.3% are male CEOs. As female-CEO firms tend to be smaller than male CEOs (Table 1), the fraction of female CEOs is only 3.4% among large firms. This share increases as the firm size reduces, although female CEOs make up only 6.2% among small-sized firms. See Appendix Table A4 for the official definition of the firm-size categories in Japan.

suppliers and buyers and k denote an index of an arbitrary market segment in K.[14] As some industry pairs have no transactions, there are approximately 5,000 markets per year. We indicate alternative definitions of markets in Section 3.5.3. Define the set S^k of suppliers in market k as the set of firms trading at least once as a supplier in the market in the year. Then,

$$S^k = S^k_f \cup S^k_m,$$

where S^k_g is the set of suppliers in market k with CEO gender $g \in \{f, m\}$ where f and m represent female and male, respectively. Similarly, we define the set B^k of buyers

$$B^k = B^k_F \cup B^k_M,$$

with the buyers' gender in capital letters to distinguish it from the suppliers' gender.

Consider a network of suppliers and buyers in a given market k, where a link exists between supplier $i \in S^k$ and buyers $j \in B^k$ if one of the firms lists the other firm as a supplier or buyer. We model that the link formation between firms is generated by the following model:

$$Y_{ij} = \mathbb{I}\{\beta_h \times SameGender_{ij} + g(X_i, X_j)'\delta + \alpha^k_i + \gamma^k_j \geq \epsilon_{ij}\}, \tag{1}$$

where Y_{ij} is a dummy variable indicating whether a link exists between supplier i and buyer j. The model states that the link formation depends on: $SameGender_{ij}$, indicating that both the CEOs of i and j are of the same gender; a vector of other pair-level observable variables $g(X_i, X_j)$, which is constructed based on firm- and CEO-specific attributes X_i and X_j; supplier fixed effect α^k_i; buyer fixed effect γ^k_j; and an unobserved idiosyncratic component ϵ_{ij}. We assume that, for any i and j, the ϵ_{ij} is independent and has a logistic distribution. In the model, we allow firm fixed effects (α^k_i, γ^k_j) to vary from market to market, but the effects of pair-level variables are assumed to be common across markets. Notably, any components additively separable in X_i and X_j will be absorbed by the terms α^k_i and γ^k_j, including any firm-related attributes (e.g., firm size, firm age, and firm culture), as well as CEO-related attributes (e.g., gender, age, education, and psychological attributes).

If $\beta_h > 0$, two firms are more likely to trade with each other if their CEOs are of the same gender compared with firms with CEOs of the opposite gender. In this case, CEO

[14] We use two-digit industry pairs to define markets because we intend to exploit within-market variation to control for supplier and buyer fixed effects in subsequent estimations. With a finer definition of markets, such variations may not be adequately ensured, potentially necessitating the exclusion of many markets.

gender homophily exists in the formation of firm-to-firm transactions. Importantly, we cannot identify *gender-specific* homophily effects, such as whether homophily is stronger for female CEOs or male CEOs. In other words, it is not possible to include both the female-to-female dummy and the male-to-male dummy simultaneously in place of the same-gender dummy in Equation (1). This is because the variation in the female-to-female dummy comes from three sources: whether i and j are CEOs of the same gender, whether i is female, and whether j is female. As the model controls for supplier and buyer FEs, the latter two sources of variation are removed, leaving only the variation associated with same-gender CEOs. Consequently, while we can identify the effect of having same-gender CEOs on transactions, we cannot determine if homophily is stronger for one gender than the other.[15]

In Section 3.3, we provide visual evidence for the *existence* of CEO gender homophily in the formation of firm-to-firm transactions: $\beta_h > 0$ in Equation (1), and in Section 3.4, we directly estimate Equation (1) to quantify the magnitude of β_h.

3.3 Relative homophily in firm-level analysis

Here, we aim to provide visually clear and compelling evidence of the presence of CEO gender homophily: $\beta_h > 0$. The following analysis is based on the notion that, if same-gender CEO bias does not exist—the occurrence of transactions is determined independently of the CEO's gender (i.e., random)—the share of transactions with female-led buyers (suppliers) should be the same regardless of the gender of the suppliers (buyers). The unit of analysis is firm (either supplier or buyer), whereby each firm is allowed to enter multiple markets.

To simplify our exposition, we focus on supplier-side analysis. The buyer-side analysis is analogous. Define, for each supplier i in market ($i \in S^k$),

$$T^k_{i,F} \equiv \frac{\sum_{j \in B^k_F} Y_{ij}}{\sum_{j \in B^k} Y_{ij}},$$

[15] More formally, we can show that

$$\mathbb{I}_{fF} = \frac{1}{2} SameGender_{ij} + \mathbb{I}_{f\bullet} + \mathbb{I}_{\bullet F} - 1,$$

where $\mathbb{I}_{fF}, \mathbb{I}_{f\bullet}, \mathbb{I}_{\bullet F}$ are dummy variables indicating female CEOs for both suppliers and buyers, female CEOs for suppliers and female CEOs for buyers, respectively.

and for each supplier's gender $g \in \{f, m\}$,

$$T^k_{g,F} \equiv \frac{1}{|S^k_g|} \sum_{i \in S^k_g} T^k_{i,F},$$

where $|S^k_g|$ denotes the number of suppliers in S^k_g. In other words, $T^k_{i,F}$ is the share of female-led buyers among all the buyers who transact with supplier i in market k, and $T^k_{g,F}$ is the average of $T^k_{i,F}$ of suppliers whose CEO gender is $g \in \{f, m\}$.[16]

We denote the *market* proportion of female buyers by $\lambda^k_F \equiv |B^k_F|/|B^k|$. If transactions between firms are completely random, $T^k_{g,F}$ and λ^k_F should, on average, coincide with each other. Thus, in most sociological literature on homophily, such as Coleman (1958), researchers determine whether CEOs of the same gender are biased to form firm-to-firm transactions if

$$T^k_{f,F} > \lambda^k_F. \tag{2}$$

However, Equation (2) does not properly capture the sign of β_h as in Equation (1). This is because female- and male-led buyers may systematically differ regarding firm size and other characteristics that could influence the occurrence of transactions. For instance, if female-led buyers are smaller in firm size and thus have less trading capacity, the share of transactions with female-led buyers in the market will be systematically lower than λ^k_F for both $T^k_{f,F}$ and $T^k_{m,F}$.

Therefore, following Zeltzer (2020), rather than examining whether Equation (2) holds, we check whether the following inequality (called *relative* homophily) holds[17]:

$$T^k_{f,F} > T^k_{m,F}. \tag{3}$$

In Appendix Section B.1 Proposition 1, we formally show that Equation (3) holds *if and only if* $\beta_h > 0$, under the condition that the characteristics of the suppliers do not differ by the gender of their CEOs. Intuitively, if there is no same-gender CEO bias ($\beta_h = 0$),

[16] To give a complete example, suppose there are five suppliers in market k, composed of three male-led suppliers and two female-led suppliers. The first male-led supplier trades with three buyers, one of which is a female-led buyer. Then, $T^k_{i,F}$ for this male-led supplier i is 1/3. This way, $T^k_{i,F}$ is calculated for all five suppliers. Then, we sum $T^k_{i,F}$ for three male-led suppliers and divide it by the number of male suppliers in the market (i.e., $|S^k_m|$= three) to calculate the average, which is $T^k_{m,F}$. Similarly, we sum such values for the two female-led suppliers and divide it by the number of female suppliers (i.e., $|S^k_f|$= two) to calculate the average, which is $T^k_{f,F}$. For each market k, we repeat the same exercise to calculate $T^k_{g,F}$ ($g \in \{f, m\}$).

[17] The concept of relative homophily has been used in other contexts such as Anwar and Fang (2006), Antonovics and Knight (2009), Zeltzer (2020), and Cabral and Dillender (2024).

the share of transactions with female-led buyers by female-led suppliers, $T^k_{f,F}$, should be equal to that of male-led suppliers, $T^k_{m,F}$. Importantly, we compare $T^k_{f,F}$ and $T^k_{m,F}$ *within* market k where the market proportion of female-led buyers λ^k_F is identical for both female- and male-led suppliers. In other words, the number of female-led buyers in the market ("exposure" in Chetty et al. (2022)) with whom both female- and male-led suppliers can *potentially* transact is the same.

First, we present visual evidence that the relationship in Equation (3) indeed holds, followed by a more formal regression analysis demonstrating that it is robust to flexibly controlling for the supplier's characteristics.

Results.—Figure 4(a) plots the share of female-led buyers in the market, λ^k_F, on the x-axis and the average share of transactions between female-led buyers and female- and male-led suppliers in the market, $T^k_{g,F}$ where $g \in \{f, m\}$, on the y-axis. Markets are defined as two-digit industry pairs and years.[18] To ensure the figure is visually comprehensible, we present a binned scatterplot of the same data with fitted linear lines weighted by market size in Figure 4(b). Bins are defined so that the number of observations in each bin is the same.

Figure 4(b) illustrates two important and novel findings. First, both fitted lines are below 45° lines, suggesting that although the share of transactions with female-led buyers increases with the market share of female-led buyers, the share of transactions with female-led buyers is, on average, lower than the market share (i.e., the random match or 45° line) for both female- and male-led suppliers. As discussed earlier, this tendency can be interpreted as reflecting the fact that female-led buyers have less trading capacity than male-led buyers due to, for example, their smaller firm size (see Table 1).

Second, and more importantly, the fitted line for female-led suppliers is above the line for male-led suppliers across almost all bins. This suggests that the average share of transactions with female-led buyers is greater for female-led than for male-led suppliers ($T^k_{f,F} > T^k_{m,F}$) for almost *any* value on the x-axis, that is, *within* the markets in which the set of potential female-led buyers is identical for both female- and male-led suppliers. This so-called *relative* homophily—essentially the vertical difference in two lines in the figure—indicates CEOs' same-gender bias in forming firm-to-firm transactions.

Next, we describe the regression analysis as Figure 4 does not control for the suppliers' characteristics, but the results are essentially the same after including controls. We

[18] The results are robust to alternative market definitions. See Appendix Figure A2.

estimate the following model:

$$\frac{T_{i,F}^k}{\lambda_F^k} = \beta_{rh} \times female_i + X_i'\delta_r + \alpha^k + u_i^k, \tag{4}$$

where $female_i$ is the dummy variable indicating that the CEO of supplier i is female, X_i is the vector of other observed supplier characteristics, α^k is the market fixed effects, and u_i^k is the idiosyncratic error. Notably, we normalize Equation (4) by dividing $T_{i,F}^k$ by λ_F^k. Therefore, we can interpret β_{rh} as representing how many percentage points closer to a random match female-led suppliers are relative to male-led suppliers (Chetty et al., 2022). Standard errors are clustered at the firm level across markets.

Table 4 summarizes the results. Column (1) only includes year FE, and Column (2) further adds year × market FEs to ensure that we compare male- and female-led suppliers *within* the same market, holding the same set of female-led buyers that male- and female-led suppliers can potentially transact with. The estimate on the female CEO dummy in Column (2) indicates that female-led suppliers are 10 percentage points closer to a random match relative to male-led suppliers ($p< 0.01$). To account for the concern of sorting of particular female-led suppliers and buyers into a particular market through gendered goods, Column (3) controls for four-digit industry FEs, the most detailed industry classification available, along with other firm characteristics, including log(employment), firm age, a dummy for being listed, credit score, and the location of the firm (prefecture FE). We are reassured that the estimate on the female CEO dummy is hardly affected. Finally, Column (4) adds a few CEO's characteristics such as age, school, and birth prefecture. This greatly reduces the sample size, but the results remain virtually unchanged.[19]

3.4 Logit—Dyad Level Analysis

Here, we directly estimate β_h in the logit Equation (1) using the dyadic data of supplier-buyer linkages as the unit of analysis instead of firm-level. The advantage of this approach over the firm-level analysis is that we can directly estimate β_h and quantify the exact impact of CEO gender homophily on transacting probabilities, allowing for counterfactual analysis later. However, there are two major challenges in estimating Equation (1) in our data. First, the estimating Equation (1) requires data on both transacting and non-transacting pairs of firms. If we consider any possible firm pairs that "might" have

[19]See Appendix Figure A4 and A5 and Appendix Table A5 and A6 for the same analyses from buyers' perspectives. We find evidence of relative homophily that is similar in magnitude.

traded, the amount of calculation would explode. With 1 million firms, there are approximately 5 billion potential supplier-buyer pairs ($_{1,000,000}C_2$), which are computationally impossible to estimate.

Second, there may be unobserved fixed effects for both suppliers and buyers: α_i^k and γ_j^k in the logit Equation (1). In our specific context, it seems essential to control for unobserved heterogeneity related to the CEO's gender, as this can introduce omitted variable bias in the estimation of gender homophily. As shown in Table 1, female-led firms tend to trail male-led firms in terms of sales, number of employees, firm age, and credit scores. Any unobserved firm characteristics that are correlated with CEO gender might also bias the standard logit estimates.[20] Notably, unobserved heterogeneity can bias logit estimates, even when omitted variables are uncorrelated with the observed variables, as emphasized by Wooldridge (2010). In fact, Graham (2017) highlights that estimates of homophily will be substantially biased if the effects of unobserved fixed effects are not accounted for when estimating the network link formation model.

We first explain how we address the second challenge. To control for unobserved fixed effects, we estimate β_h building on the insight proposed by Graham (2017), Charbonneau (2017) and Jochmans (2018). Here, we exploit the unique advantage of the supplier-buyer linkage data, which have multiple observations for the same firm at the same time period; firm i trades with firm j but not with firm j', and so on.

The following exposition follows Jochmans (2018). Set a market $k \in K$. Let us denote $W_{ij} \equiv (SameGender_{ij}, g(X_i, X_j))'$, $\theta \equiv (\beta_h, \delta)$ and rewrite the model (1) as,

$$Y_{ij} = \mathbb{I}\{W_{ij}'\theta + \alpha_i^k + \gamma_j^k - \epsilon_{ij} \geq 0\}.$$

Then, set a quadruple of distinct firms $\sigma \equiv \{i_1, i_2; j_1, j_2\}$, where $i_1, i_2 \in S^k$ and $j_1, j_2 \in B^k$, and define the random variable

$$Z_\sigma \equiv \frac{(Y_{i_1 j_1} - Y_{i_1 j_2}) - (Y_{i_2 j_1} - Y_{i_2 j_2})}{2},$$

and let $R_\sigma \equiv (W_{i_1 j_1} - W_{i_1 j_2}) - (W_{i_2 j_1} - W_{i_2 j_2})$. Note that Z_σ can take on values from the set $\{-1, -1/2, 0, 1/2, 1\}$. Assuming that ϵ_{ij} are independent and identically distributed

[20] For example, female and male CEOs may have different management skills due to their different backgrounds and experience (Kepler et al., 2007; Fairlie and Robb, 2009). Regarding the CEO characteristics associated with gender, literature in experimental economics suggests that, compared to men, women are less willing to take risks (Eckel and Grossman, 2002), less confident and competitive (Niederle and Vesterlund, 2007), and more reluctant to negotiate (Babcock and Laschever, 2009) than men. Women are also known to have less access to personal and professional networks (Koellinger et al., 2013) and spend less time networking due to household chores (Azmat and Ferrer, 2017).

following the standard logistic distribution, Charbonneau (2017) and Jochmans (2018) show that the conditional probability of $Z_\sigma = 1$ given $Z_\sigma \in \{-1, 1\}$ is expressed as

$$\Pr(Z_\sigma = 1 \mid R_\sigma, Z_\sigma \in \{-1, 1\}) = \frac{\exp(R_\sigma'\theta)}{1 + \exp(R_\sigma'\theta)}.$$

This formulation leads to the following conditional likelihood function, which we maximize to estimate $\theta = (\beta_h, \delta)$:

$$\arg\max_\theta \sum_{k \in K} \sum_{\sigma \in \Sigma^k} \left[\mathbb{I}\{Z_\sigma = 1\} \log \frac{\exp(R_\sigma'\theta)}{1 + \exp(R_\sigma'\theta)} + \mathbb{I}\{Z_\sigma = -1\} \log \frac{1}{1 + \exp(R_\sigma'\theta)} \right],$$

where Σ^k denotes the set of all quadruples within market $k \in K$. Note that the estimation method above is a *within-year* difference-in-difference (DID) approach that uses specific network variations of the network data (quadruples with $Z_\sigma \in \{-1, 1\}$).[21]

The variation used in this method is illustrated in Figure 7. On the one hand, suppose that supplier i_1 is trading with buyer j_1 and not with buyer j_2. Here, the buyer changes from j_1 to j_2, and supplier i_1's decision changes from 'trade' to 'do not trade.' There are two main reasons for this change: (i) change in pair-level covariates (i.e., $W_{i_1 j_1} - W_{i_1 j_2}$), and (ii) change in the fixed effect between buyer j_1 and buyer j_2 (i.e., $\gamma_{j_1}^k - \gamma_{j_2}^k$). On the other hand, let us assume that supplier i_2 is not trading with buyer j_1, but is trading with buyer j_2. In this case, the buyer has changed from j_1 to j_2, and supplier i_2's decision has changed from 'do not trade' to 'trade.' As aforementioned, there are two possible factors for this change in decision-making: (i) change in pair-level covariates (i.e., $W_{i_2 j_1} - W_{i_2 j_2}$), and (ii) change in the fixed effect of buyers j_1 and j_2 (i.e., $\gamma_{j_1}^k - \gamma_{j_2}^k$). However, for the latter, suppliers i_1 and i_2 face the same sequence of buyers (j_1 and j_2). Therefore, the *difference* in the change in decision-making between suppliers i_1 and i_2 is

$$Z_{\sigma\{i_1, i_2; j_1, j_2\}} = \frac{(Y_{i_1 j_1} - Y_{i_1 j_2}) - (Y_{i_2 j_1} - Y_{i_2 j_2})}{2},$$

and can be attributed as being brought by the difference in the change in pair-level

[21] A typical DID utilizes the data structure in which multiple observations are available for a single unit across multiple time periods ("panel" in time). In our context, this means observing firms over multiple time periods and utilizing *changes* in the gender of CEOs within the same firm *over time*. We are hesitant to use such a variation because paths to becoming CEOs differ across CEOs' genders, making it likely to be endogenous (see Appendix Figure A6). Thus, we utilize a "panel" structure driven by the network data *within-year*. Namely, firm-to-firm transaction data have *multiple* observations for the same firm at the same time period, i.e., firm i_1 trades with firm j_1 but not with firm j_2, and so on. Utilizing these across-pair variations allows us to control for all fixed effects in the same time period for a single firm.

variables:

$$R_{\sigma\{i_1,i_2;j_1,j_2\}} = (W_{i_1j_1} - W_{i_1j_2}) - (W_{i_2j_1} - W_{i_2j_2}),$$

netting out supplier and buyer FEs.[22]

While this method successfully addresses the second challenge related to unobserved fixed effects, the first challenge regarding computational feasibility remains. Specifically, if we consider all possible quadruples in our sample, it would be of order 10^{28} quadruples, which is impossible to estimate. To eliminate this issue, we perform the estimation by drawing a 5% random sample from all possible quadruples with $z_\sigma \in \{-1, 1\}$.

Results.—Table 5 shows the estimation results of Equation (1). Due to computational limitations, we report the estimates using only 2019 data for now. Column (1) shows that the estimate on the same-gender CEO dummy is 0.051 ($p < 0.01$), which indicates that the probability of the transactions is 5.1% higher among CEOs with the same gender relative to the transactions with the opposite gender.[23] Column (2) adds the log of the distance between suppliers and buyers, as well as a dummy indicating whether a large firm is involved in the pair (either as supplier or buyer); the estimates remain robust.

Thus far, we only include the distance between suppliers and buyers as $g(X_i, X_j)$ other than $SameGender_{ij}$ in Equation (1). The concern is that the coefficient on the same-gender dummy captures the effect of other homophily that are correlated with gender homophily. For instance, the summary statistics in Table 1 show that female CEOs are less educated than male CEOs. Thus, it is possible that gender homophily may capture the effect of homophily through education. To account for this concern, we add other homophily variables to determine whether the estimate on gender homophily is attenuated.

Our preferred specification (Column (3) of Table 5) adds the pair-level covariates constructed by *firm characteristics*, namely, a dummy for both firms to be located in the same prefecture and to be listed, the absolute difference of log(employment), firm age, and credit score between firms. The estimate on the same-gender CEO dummy is hardly affected. Column (4) further adds the pair-level covariates constructed by *CEO characteristics*, namely, the absolute difference in CEO age, a dummy for both CEOs

[22]It should be noted that the explanation provided here is a general idea of how FEs are controlled using within-year variation in pair-level data and is not limited to the logit model.

[23]The provided estimates represent odds ratios. However, due to sparsity, we can interpret estimates close to zero as approximately equal to the percentage increase in probability compared to the opposite gender case, that is, around zero, $\beta_h \approx (p_{ij}|SameGender_{ij} = 1)/(p_{ij}|SameGender_{ij} = 0) - 1$. See Appendix Section B.2 for details.

to be born in the same prefecture, have attended the same school, and have the same family name (to capture the transactions within the family). While the homophiles in CEO's characteristics along these dimensions are clearly observed in Column (4), the estimate on the gender homophily remains robust and even larger in magnitude at 0.09. As the sample size in Column (4) is largely reduced by 4/5 from the baseline sample in Column (1) due to the missing CEO attributes, Column (5) uses the same subsample as Column (4) but drops variables on homophiles in CEO's characteristics altogether. The estimates on the CEO same-gender CEO dummy between (4) and (5) are similar, suggesting that the larger estimate in Column (4) is due to the sample selection. In any case, we are reassured that including all possible homophily variables in our data other than gender hardly attenuates the estimate on the gender homophily. This suggests that the estimate on the same-gender CEO dummy we have documented so far indeed reflects the gender match of CEOs rather than other factors correlated with gender.

3.5 Additional evidence

We conduct a series of additional analyses to further substantiate our findings on CEO gender bias in inter-firm transactions.

3.5.1 Heterogeneity by firm-size

As a firm becomes larger, one can expect that the firm's decision-making process is delegated from top management to middle- and lower-level managers. Therefore, if our results are indeed driven by CEOs' involvement in transaction formation processes (e.g., finding a partner, negotiating deals), the CEO gender homophily should be more pronounced in relatively smaller firms. Figure 5(a) confirms, based on our own survey data, that the CEOs of smaller firms are much more likely to attend negotiation meetings than those of larger firms. Of CEOs in small-sized (large-sized) firms, 58.4% (6.9%) attend all transactions, whereas 14.0% (37.6%) rarely become involved in any transactions.

We start with a visual examination of relative homophily by firm size. Figure 6 repeats Figure 4 for large firms (27% of all transactions) in Panel (a) and SMEs (73% of all transactions) in Panel (b).[24] On the one hand, Panel (a) does not reveal any evidence of gender homophily among large firms; two lines of female- and male-led suppliers are almost identical to each other. On the other hand, Panel (b) indicates a clear pattern of

[24]See Appendix Table A4 regarding the definition of large-, medium-, and small-sized firms, which is defined by the number of full-time employees and capital stock in each industry in Japan. As the information on capital stock is not complete in our data, we only use the number of full-time employees to define the firm size.

gender homophily among SMEs. Panels (c) and (d) further divide SMEs into medium- and small-sized firms. While both figures strongly support the evidence of relative homophily, it is stronger in small-sized firms than medium-sized firms, consistent with our survey observation that CEOs of smaller firms are more likely to sit at negotiation tables, and hence the gender of CEO could be more crucial.

We now use a logit model to formally analyze the heterogeneity by firm size. Columns (1)-(3) of Table 6 report the heterogeneity by firm size from estimating the variant of Equation (1), which further includes the interaction of a same-gender CEO dummy with a dummy for the firm-size category. For ease of comparison, Column (1) replicates Column (3) of Table 5. Column (2) adds the interaction of a same-gender CEO dummy and a large-involved dummy. Thus, a same-gender CEO dummy represents the estimate among SMEs, which is 0.080 ($p < 0.01$) and is much larger than that for all firms in Column (1). Furthermore, the estimate of the interaction term is negative, and the magnitude is similar to the one for the same-gender CEO dummy (-0.072), suggesting that there is no gender homophily for trade involving large firms. Indeed, the p-value for the null hypothesis for gender homophily for large-involved trade is 0.396, as shown in the last row of the table. Column (3) adds the same-gender CEO dummy and a dummy indicating that the pair contains either large or medium firms, such that the same-gender CEO dummy now represents the estimate of gender homophily among small-sized firms. The estimate is 0.109 ($p < 0.01$) and is larger than that for all firms in Column (1) and SMEs in Column (2). Among small-sized firms, the estimate indicates that the probability of transactions with CEOs of the same gender is 10.9% higher than that of transactions with the opposite gender.

Thus far, we report the estimate using only 2019 data. To ensure that the 2019 estimates are similar to those for other years, Figure 8 plots the estimates across the years, separately for transactions of large-involved (Panel (a)) and those of SMEs (Panel (b)). Here, each estimate in each year comes from a separate regression. Reassuringly, the estimates are more or less stable over time, both overall and by firm size. Notably, for large-involved transactions, the estimated CEO gender homophily remains close to zero across the years. By contrast, for SMEs, the estimates consistently indicate that the probability of trade is approximately 10% higher when CEOs are of the same gender compared with those of opposite genders.

The result that CEO gender homophily is stronger for transactions among smaller firms suggests that CEO involvement in transaction decisions may be a source of CEO gender homophily. Furthermore, the lack of gender homophily in transactions where large firms are involved implies that our results are not driven by a firm culture, which

can be well correlated with CEO gender.

3.5.2 Hobby

The results from Section 3.5.1 reveal stronger gender homophily between small firms, while such gender homophily does not exist in transactions where large firms are involved. Given that CEOs in smaller firms are more likely to engage in transactions among themselves, CEO-level networking may be crucial in forming firm-to-firm transactions (Cai and Szeidl, 2018; Asiedu et al., 2023). We further elaborate on this point using novel data on CEOs' *hobbies*.

Recent literature has demonstrated that gender differences in social networking tools are associated with the gender gap in the labor market. Cullen and Perez-Truglia (2023) provide evidence that men's access to key social networking tools, such as chatting over smoking and playing golf, with influential men contributes to their higher promotion rates compared with women. Additionally, Agarwal et al. (2016) find that women's participation in golf, a predominantly male social activity, significantly increases their chances of serving on a board of directors.

The TSR data records CEOs' hobbies (up to three), and Figure 9 illustrates a striking gender difference in the distribution of CEO hobbies. Approximately 46% of male CEOs list "Golf" as their hobby, representing a substantial majority. By contrast, approximately 16% of female CEOs cite "Golf" as a hobby, a relatively higher percentage but not the most prevalent (with "Travel" being the most common hobby before "Golf" among female CEOs). If CEOs establish connections and deepen friendships through shared hobbies, could this be a factor underlying our results?

Table 7 tests this hypothesis. Column (1) provides the baseline estimate using data with available CEO hobbies. Column (2) adds a dummy for shared hobbies, showing that CEOs with common hobbies are approximately 4% more likely to trade. Column (3) further includes an interaction term for shared hobbies and gender homophily to assess whether hobby similarity boosts transactions regardless of gender. Interestingly, the results suggest that the effect in Column (2) arises only when CEOs share both gender and hobbies. The shared hobby dummy in Column (3) is near zero (-0.006) and statistically insignificant, indicating that shared hobbies alone do not drive trade between opposite-gender CEOs.[25]

While these findings are definitely suggestive at best, they imply that the problem lies not in gender differences in the social networking tool of hobbies but rather in the

[25]Our companion paper, Izumi et al. (2024), shows that playing golf is unlikely to help female CEOs find male business partners.

exclusive structure in which contributing to networking and bonding through shared hobbies occurs only among CEOs of the same gender. This is in contrast to the finding by Agarwal et al. (2016) but aligns with the widely discussed phenomenon of the "old boys (or girls) club" in recent literature (e.g., Michelman et al., 2022; Cullen and Perez-Truglia, 2023).

3.5.3 Robustness to alternative market definitions

Although our main analysis defines markets using two-digit industry pairs, there remains a potential concern that the observed CEO gender homophily might reflect differences in the industry composition of female- and male-led firms within a broadly defined market. For example, female CEOs may operate in separate sub-markets within two-digit industry pairs with distinct pools of potential trading partners, or female- and male-led firms might trade different types of goods, as the TSR data lack detailed information on the traded goods.

To address this concern, we narrowly redefine market classifications using three- and four-digit industry pairs and re-estimate Equation (1). By enhancing the homogeneity of industries and, consequently, the goods traded within narrower markets, we aim to test the robustness of our findings.

Appendix Table A7 shows that estimates on the CEO same-gender effect are hardly affected after refining either the supplier- or buyer-side industry classification. These findings confirm that the CEO same-gender effect is robust to alternative market definitions, alleviating concerns that the results are driven by differences in the types of goods traded.

3.5.4 Duration analysis

An alternative explanation for our findings on CEO gender bias is that transactions between same-gender CEOs may last longer than those between opposite-gender CEOs, leading to overrepresentation in the data. To address this concern, we conduct a duration analysis focusing on newly formed firm-to-firm transactions. Specifically, we restrict our analysis to supplier-buyer pairs formed in or after 2009 to avoid left-censoring, as our original sample starts in 2008, and calculate the duration of each transaction.[26] If CEO gender homophily primarily arises during the continuation stage of transactions, we would expect that the transaction duration for same-gender CEO pairs would be longer than that for opposite-gender CEO pairs.

[26] Additionally, we exclude pairs in which the CEO of either the supplier or the buyer changed after the transaction began to eliminate the potential influence of CEO turnover.

Figure 10 shows Kaplan-Meier survival curves comparing the duration of transactions between same-gender and opposite-gender CEO pairs. The figure shows no clear difference in the duration of transactions based on the CEO gender match. A Cox proportional hazard regression further confirms that whether CEOs are of the same gender does not significantly influence the transaction duration, even after controlling for firm- and pair-level characteristics (Appendix Table A8). This finding reinforces the interpretation that CEO gender homophily is predominantly a formation-stage phenomenon. In other words, homophily appears to reflect barriers or biases that affect the likelihood of transactions being formed, rather than differences in their stability once established.

That said, it is important to acknowledge the potential role of selection bias. While the duration analysis demonstrates that the gender match of CEOs does not affect the duration *conditional on* transactions being formed, it does not rule out the possibility that opposite-gender transactions are less likely to form in the first place due to concerns about their potential instability. For example, if cross-gender transactions are perceived to be inherently short-lived—perhaps due to difficulties in building trust or effective communication—this perception could discourage their formation altogether.

These findings highlight the need for understanding the mechanisms driving homophily at the formation stage. To investigate this further, we turn to our CEO survey, which explores whether homophily stems from structural frictions, such as limited opportunities for cross-gender interactions, or preferences, such as an explicit bias for same-gender collaborations.

4 Survey evidence

While the analysis of supplier-buyer relationship data provides solid evidence that CEO gender homophily exists in firm-to-firm transactions, it does not address the underlying mechanisms. In general, homophily may arise from two sources that can operate simultaneously: biases in the likelihood of meeting similar individuals (homophily in "meetings") and biases in individuals' preferences for interacting with similar others (homophily in "preferences") (e.g., Currarini et al., 2009). Such distinction is important because the policy and welfare implications differ significantly depending on the nature of each source. When the latter (homophily in "preferences") is a factor, public policy has limited capacity to intervene in individual preferences. Furthermore, if preference-based homophily results from lower communication costs between individuals of the same gender, it may increase the value of collaboration. However, if it stems from taste-based discrimination toward the opposite gender, it could promote inefficient trade formations.

Thus, in cases in which preference-based homophily is significant, the welfare impact is complex and may be ambiguous. While these considerations highlight the importance of disentangling these mechanisms, we refrain from definitive claims about the welfare implications or policy interventions in this study.

By contrast, the presence of homophily in "meetings" offers a clear policy opportunity. Government interventions could help reduce this bias by influencing meeting technologies—such as organizing business-matching events or operating matching platforms that facilitate connections between CEOs of different genders. Policies that remove such frictions and make it easier for CEOs of different genders to meet would likely be welfare-enhancing.

4.1 Settings

To this end, we conduct our original survey of CEOs in collaboration with the Cabinet Office of the Government of Japan.[27] In February 2023, we randomly selected 12,500 each female and male CEOs (25,000 in total) identified from TSR's database and sent them a physical survey by mail. To ensure consistency with the sample in our main analysis, the targeted population was limited to firms whose CEO gender, sales, number of employees, firm age, and credit score were non-missing in the database and were engaged in firm-to-firm transactions. Respondents were allowed to answer the survey on paper or access a link to answer it online. Ultimately, we received responses from 3,082 female and 3,355 male CEOs, with an overall response rate of 25.7% (N= 6,437), which can be regarded as exceptionally high given that the response rates of CEO surveys ranged from 9% to 17% in previous studies (Graham et al., 2013; Bandiera et al., 2020).

To measure homophily in "meetings," we posed the following question to respondents: *"Please think of one CEO with whom you have been acquainted most recently. Please indicate the gender of that person."* Respondents chose either 'female,' 'male,' or 'other gender.' Although we could have asked for the gender ratio of CEOs they met over the past year, such questions may impose an excessive cognitive burden and lead to inaccurate answers. Therefore, we focused on the gender of the *most recently* acquainted CEO. If the probability of meeting a female CEO differs between female and male respondents, a gender difference should be observed in the proportion of respondents who answered 'female' to this question. However, even if a gender difference in "meetings" is observed,

[27] Currarini et al. (2010) uses structural estimation to identify the extent of meeting bias and preference bias in friendship formation. However, their approach relies on simplifying assumptions in the model, and they recognize that it does not clearly separate how much of the meeting bias originates from preferences. With the cost of deviating from a revealed-preference approach, we use survey methods to demonstrate that some part of the meeting bias can be explained by preferences.

it remains unclear whether this difference arises from actual *frictions* that make it difficult for opposite-gender CEOs to meet or from a tendency among male CEOs to avoid seeking out female CEOs due to personal preferences.

Therefore, our "preference" questions were designed to satisfy two objectives. The first is to control for homophily in "meetings" owing to respondents' willingness to meet female CEOs ("choice" part). For this purpose, we asked, *"If you could become acquainted with a new CEO, would you like to get to know a male or female CEO, or it does not matter?"*[28] The second set of questions was designed to measure homophily in "preference" *conditional on* already meeting CEOs by asking about impressions during interactions and business meetings with CEOs. In particular, we asked whether each of the following seven incidents (both positive and negative) is more likely to occur with male CEO or female CEO or equally likely to occur regardless of CEO gender: *"easier to talk business-related concerns with," "easier to negotiate business deals with," "easier to interact with," "talked down to you," "did not listen to you seriously," "pressure to follow gender stereotypes,"* and *"more concerned about the other's task ability."* For these questions, respondents chose from 'female,' 'male,' or 'neutral.'

In addition to meeting- and preference-related questions, the survey asked the following: how much the respondent is involved in the business negotiation of firm-to-firm transactions (Section 3.3); pathways to becoming CEOs (Appendix Figure A6); the respondent's basic attributes such as years of business experience and hours of business per week; and psychological attributes such as competitiveness, risk attitude, and self-confidence (Dohmen et al., 2011; Buser et al., 2024). Finally, to ensure that primacy bias does not influence our results, we randomly assigned the order of gender ('female' or 'male') to appear first in each gender-related question.

4.2 Sample characteristics

Table 8 summarizes respondents' basic information by gender of respondents and reproduces the analogous statistics observed in our TSR data. The table presents a new finding (not available in TSR data) that women have fewer years of business experience and work fewer hours per week compared with men. Additionally, female CEOs tend to be less competitive, more risk-averse, and less self-confident than their male counterparts. While such gender differences in psychological attributes have been widely documented (e.g., Bertrand, 2011), the table shows that these patterns also hold among CEOs.

[28] Additionally, we let respondents assume that other conditions such as firm size and type of business are the same, such that we can elicit pure preference for gender.

Appendix Table A9 compares the characteristics of respondents and non-respondents. While respondents tend to manage firms with higher firm age, lower listing ratios, and higher credit scores, these differences are generally small. Notably, the differences in sales and employment are not statistically significant, even with a large sample size. Thus, we consider the selection issue negligible.[29]

4.3 Results

First, we separately examine homophily in "meetings" and "preferences". Then, we run a regression to test whether homophily in "meetings" persists after accounting for homophily in "preferences" and other potential confounders.

Descriptive analysis.—First, we examine homophily in "meetings." Figure 11 plots the probability that the respondent became recently acquainted with a female CEO over the respondents' gender. Notably, the probability is 19.9% for female respondents but only 5.2% for male respondents, which is less than one-third of the probability for female respondents. Essentially, the actual proportion of female CEOs in the raw data of the TSR in 2022 is approximately 14.4%. This comparison suggests that female respondents are more likely to become acquainted with female CEOs than expected by random chance (19.9% >14.4%), whereas male respondents are more likely to become acquainted with male CEOs than expected by random chance (5.2% <14.4%).

Next, we examine homophily in "preferences." Figure 12 summarizes responses to the preference-related questions. For each question, we report the difference in the share of respondents who selected male and female, along with its 95% confidence interval, by each gender of the respondents. This is equivalent in coding to 1 if the respondent selects male, 0 if the respondent is neutral, and -1 if the respondent selects female. Thus, larger positive values indicate a bias toward males, larger negative values indicate a bias toward females, whereas 0 values mean neutral.

The results collectively show that female respondents have a neutral preference for CEO gender, while male respondents tend to prefer male CEOs. The first line of Figure 12 addresses the "choice" part of homophily in "preferences." The male respondents, who would prefer to become acquainted with a male CEO, were 19.5 percentage points higher than those who would like to become acquainted with a female CEO. However, female respondents who preferred to get acquainted with a female CEO were only slightly higher than those who preferred to become acquainted with a male CEO, with a differ-

[29] Consistent results are also obtained from a robustness check using weighted analyses (available upon request).

ence of 6.9 percentage points, which is modest compared to the larger difference among male respondents.

The subsequent lines in Figure 12 measure the "preferences" conditional on meeting other CEOs separately by the gender of respondents by asking about the expectations in the interactions with CEOs. The subsequent three lines refer to *positive*, and the subsequent four refer to *negative* expectations.

We find that male respondents expect positive interaction with male CEOs, whereas female respondents' expectations are more or less neutral. For instance, male respondents expect that male CEOs are 46.6 percentage points "easier to talk about business-related concerns with," 35.1 percentage points "easier to negotiate business deals with," and 26.9 percentage points "easier to interact with" compared with female CEOs. By contrast, female respondents are closer to having no bias for the same questions. The notable exception is that female respondents perceive that male CEOs are 19.8 percentage points "easier to negotiate business deals with" than female CEOs, which is a large magnitude.

The last four lines of Figure 12 on negative interactions suggest that both female and male respondents equally expect that interactions with male CEOs are more likely to result in uncomfortable events ("talked down to you," "did not listen to you seriously," and "pressure to follow gender stereotypes"). The only exception is "more concerned about the other's task ability" (the last row), where both male and female respondents are almost neutral. This result suggests that our finding on CEO gender homophily in firm-to-firm transactions is not driven by beliefs that the opposite gender is less capable, whether those beliefs are accurate or inaccurate (e.g., Bohren et al., 2023).

Overall, we conclude that, compared with female respondents, male respondents have a stronger same-gender preference and expect better interactions with male CEOs. However, female respondents are relatively neutral towards the gender of CEOs, but they perceive that it is somewhat easier to conduct business deals with male CEOs than with female CEOs. This contrasts with the pattern observed by Ashraf et al. (2023) in Zambia, where women tend to avoid interactions with men due to fears of expropriation. This contrast underscores that the mechanisms at play in our context are fundamentally different.

Regressions.—The gender differences in the probability of becoming acquainted with female CEOs (homophily in "meetings") do not necessarily indicate the existence of friction for female CEOs to encounter male CEOs (or vice versa) because it is possible that female (male) CEOs simply prefer to meet with other female (male) CEOs. Thus, we investigate whether homophily in "meetings" persists after controlling for homophily in "preferences" (in particular, "choice" part of "preference"). If so, we can attribute the

remaining homophily in "meetings" to frictions that make it difficult for opposite-gender CEOs to meet, where government intervention can be practically effective.

Table 9 presents the regression results in which the dependent variable is a dummy variable indicating the CEO with whom the respondent became recently acquainted with is female (our variable on homophily in "meetings"), and the main explanatory variable of interest is a dummy variable indicating that the respondent is a female CEO.

Column (1) of Table 9 includes only a survey dummy, which controls the order of gender in gender-related questions, and the estimate shows that female respondents are 13.8 percentage points more likely than male respondents to meet with female CEOs ($p < 0.01$). This completely matches the difference in bar height between female (19.9%) and male (5.2%) respondents in Figure 11. The other columns sequentially add other potentially confounding variables.

Column (2) adds all the dummy variables for the responses to preference-related questions, including "choice" part of "preference." This reduces the estimate on female CEO dummy from 13.8 in Column (1) to 8.7 percentage points (37%). However, the estimate on female CEO dummy remains statistically significant at the 1% level. Column (3) adds two-digit industry FEs and prefecture FEs to account for potential differences in exposure to female CEOs across industries and prefectures. This further reduces the estimates to 7.6 percentage points, but remains statistically significant ($p < 0.01$). Column (4) adds firm-level characteristics, and Column (5) further controls for CEO attributes such as education, years of business experience, hours of business per week, competitiveness, risk attitude, and confidence. These variables are included to account for gender differences in the opportunities due to firm-level and CEO attributes. However, the results remain virtually unchanged from Column (3).

In sum, the estimate on female CEO dummy decreases from 13.8 in Column (1) to 7.6 percentage points in Column (5) after controlling for homophily in "preferences" and other confounding factors, but remains highly statistically significant ($p < 0.01$). This remaining gender difference of 7.6 percentage points is larger than the baseline probability for male respondents of becoming acquainted with female CEOs, which is approximately 5.2% (Figure 11). Therefore, most of the gender homophily in "meetings" seems to result primarily from social barriers to encountering CEOs of the opposite gender, rather than from preferences alone.

5 Discussion and Conclusion

Using a novel dataset on supplier-buyer linkages and CEO characteristics in Japan, this study shows that transactions are more likely to occur between firms whose CEOs are of the same gender. This pattern is particularly pronounced among small firms whose CEOs are presumably more involved in transaction formation. Given the current male dominance among CEOs, this gender homophily disproportionately limits trading opportunities for female-led firms.

To quantify the implications of this finding, we conduct a back-of-the-envelope counterfactual simulation to evaluate how reducing CEO gender homophily would affect the number of transactions (Counterfactual 1). Table 10 presents the results of this exercise. Details on the implementation are available in Appendix Section B.3. As a comparison, we consider a counterfactual in which the CEO gender ratio is 50-50 but gender homophily persists at current levels and evaluate its impact on *existing* female- and male-led firms (Counterfactual 2).

The results yield two key insights. First, eliminating gender homophily (Counterfactual 1) leads to an increase in transactions for both female- and male-led firms: a 6.00% rise for female-led firms and a marginal 0.22% increase for male-led firms. More importantly, this scenario reduces the gender gap in transactions by 7.76% while also increasing the overall volume of firm-to-firm transactions. These findings formally support our core claim: CEO gender homophily acts as a constraint on trading opportunities, particularly for female-led firms.

By contrast, achieving gender parity among CEOs without addressing homophily (Counterfactual 2) results in a 1.22% increase in transactions for female-led firms, but a 3.49% decrease for male-led firms, as they now make up a smaller share of the market. While this scenario also reduces the gender gap (by 9.99%), it comes at the cost of reducing total transactions, especially for male-led firms. Moreover, the benefit to female-led firms is much smaller than in Counterfactual 1. This difference between the two scenarios arises because eliminating homophily expands transaction opportunities throughout the market, such as allowing female-led firms to more easily transact with the majority of male-led firms. By contrast, equalizing the CEO gender ratio only increases the number of potential same-gender partners for female CEOs, but the barrier of homophily itself remains. Consequently, women's opportunities are only partially expanded; even with gender parity, they still account for only half of the market, leaving the majority of male-led firms effectively inaccessible due to persistent homophily.

While promoting female leadership through affirmative action remains an important

strategy to reduce gender disparities, our findings suggest that directly mitigating CEO gender homophily is essential for achieving a more inclusive and efficient market without reducing total trade volume.

Understanding the underlying mechanism that drives CEO gender homophily is critical in designing policies to mitigate such bias. Our large-scale survey of CEOs reveals that homophily operates through two main channels: (i) homophily in "meetings," whereby CEOs are more likely to encounter others of the same gender; and (ii) homophily in "preferences," wherein CEOs explicitly prefer to collaborate with same-gender counterparts. Importantly, we show that a substantial portion of homophily in "meetings" cannot be explained by "preferences" alone, suggesting the presence of structural frictions, such as gendered networks, limited opportunities for cross-gender interactions, and social norms that make cross-gender engagement less comfortable.

These insights point to clear policy implications. While homophily in preferences may reflect either efficient sorting—such as better communication with same-gender partners—or discriminatory bias, its welfare implications are inherently ambiguous and less amenable to policy intervention. By contrast, homophily in meetings stems from structural frictions that limit cross-gender encounters, making it a more concrete and actionable target for public policy.

A range of policies could help mitigate such frictions and foster more diverse business relationships: algorithmic business matching platforms that recommend partners based on complementary needs rather than personal networks; inclusive networking events that proactively promote gender-balanced interactions; and structured mentorship or peer exchange programs that pair male and female CEOs across industries could help foster more diverse business relationships. Such initiatives not only promote gender equity but also enhance market efficiency by unlocking trading opportunities that are currently restricted by social and structural barriers.

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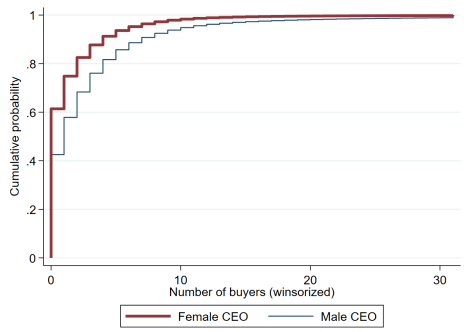
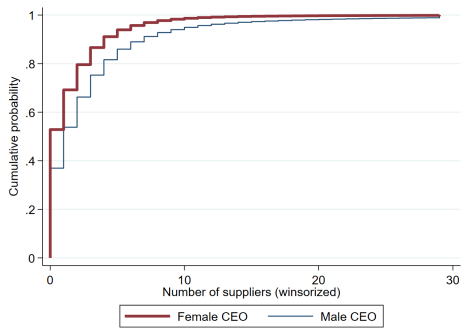
Figure 1: Network Size by CEO Gender

(a) Number of buyers



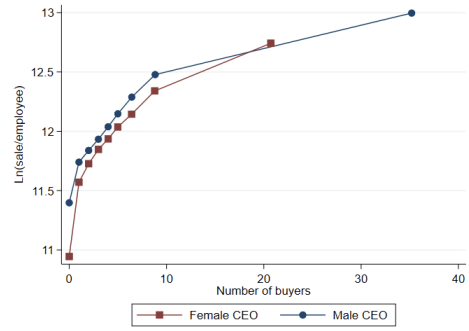
(b) Number of suppliers



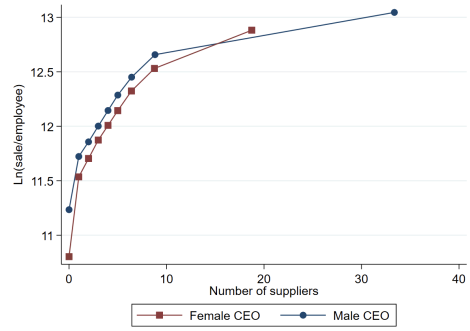
Notes: These figures show the cumulative distribution function of the number of buyers (a) and suppliers (b) by CEO gender. Both variables are winsorized at the 99th percentile. The sample is derived from the TSR data for the period 2008 to 2020.

Figure 2: Network Size and Firm Performance

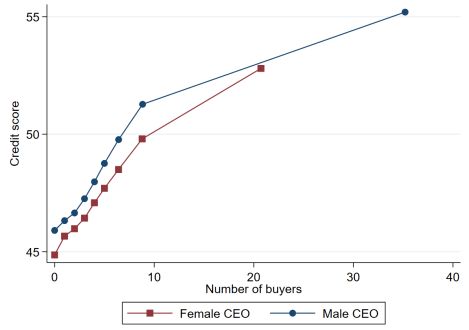
(a) Number of buyers and log sales per employee



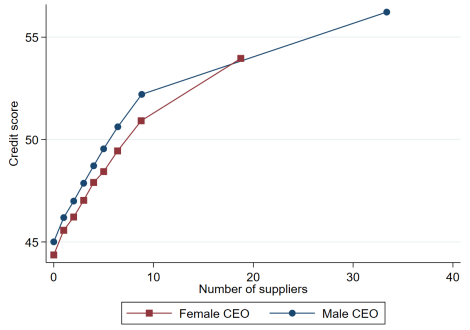
(b) Number of suppliers and log sales per employee



(c) Number of buyers and credit score

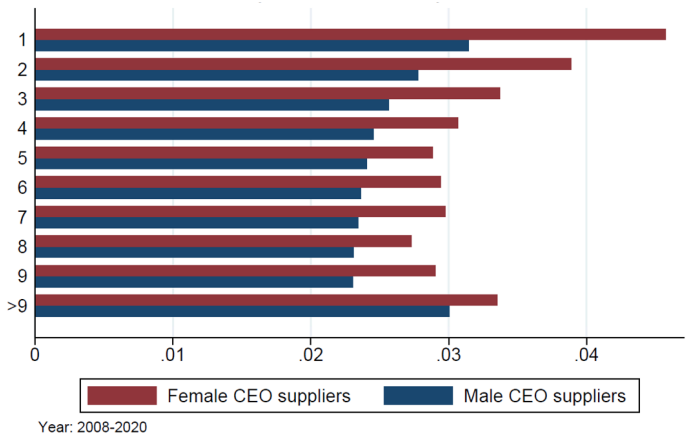


(d) Number of suppliers and credit score



Notes: These figures show the binned scatterplots of the relationship between network size (the number of suppliers and buyers) and firm performance measures, separately by CEO gender. Firm performance is measured by log sales per employment in (a) and (b) and by credit scores in (c) and (d). The sample is derived from the TSR data for the period 2008 to 2020.

Figure 3: Share of Female CEO Buyers by Total Number of Buyers

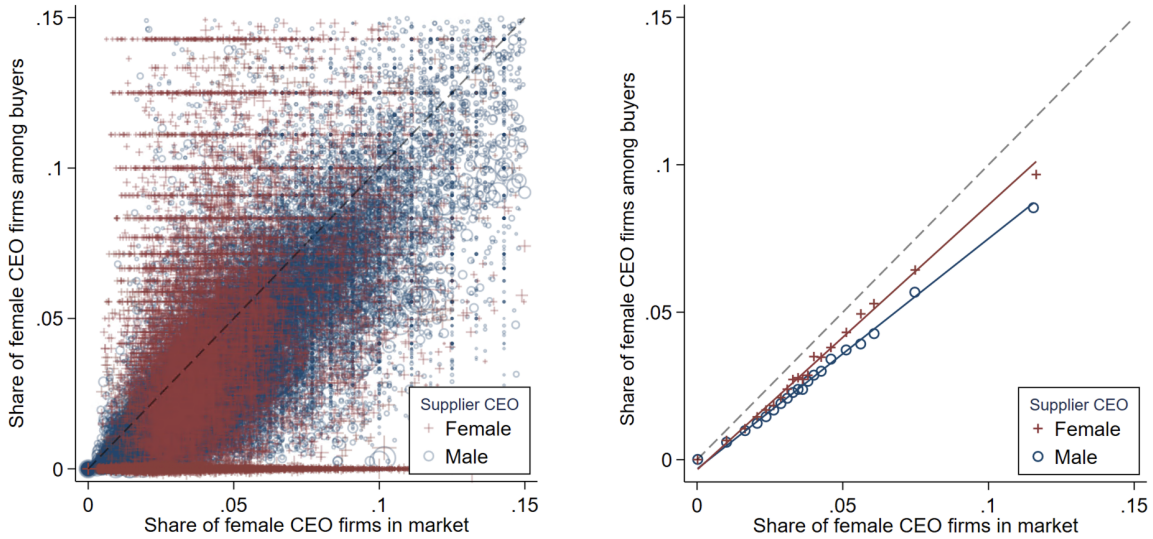


Notes: This figure shows the share of female CEO buyers by the total number of buyers, for female CEO suppliers and male CEO suppliers separately. The sample is derived from the TSR data for the period 2008 to 2020.

Figure 4: Relative Homophily

(a) Raw data

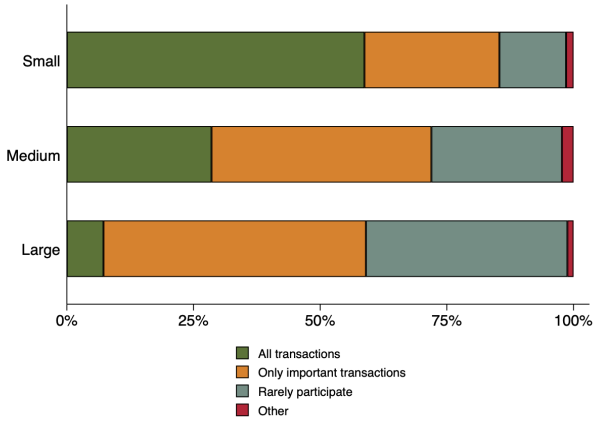
(b) Binned scatterplot



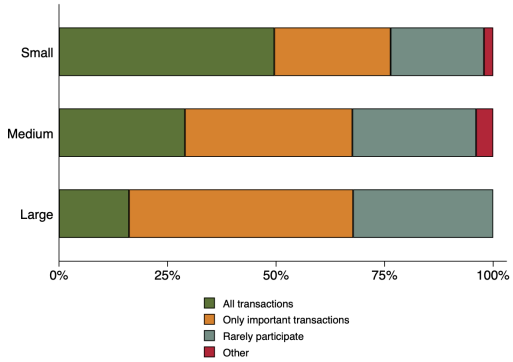
Note: This figure plots the share of female CEO buyers in the market, λ_F^k, on the horizontal axis and the share of transactions with female CEO buyers and female-CEO and male-CEO suppliers in the market, $T_{g,F}^k$ where $g \in \{f, m\}$, on the vertical axis. Markets are defined as two-digit industry pairs and years. Panel (a) presents raw data, and panel (b) presents a binned scatterplot of the same plot with regression linear lines weighted by market size. Bins are defined such that the number of observations in each bin is the same. The 45° dotted line indicates the random match. The sample is derived from the TSR data for the period 2008 to 2020.

Figure 5: Survey: CEO Involvement in Transactions by Firm-size

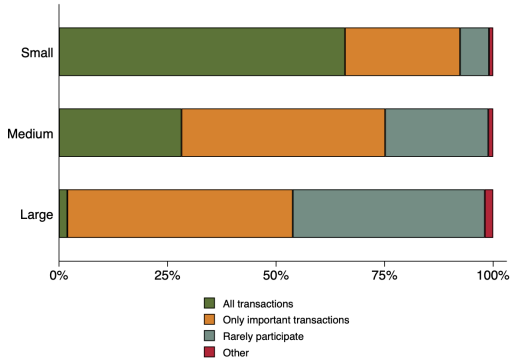
(a) All CEO



(b) Female CEO



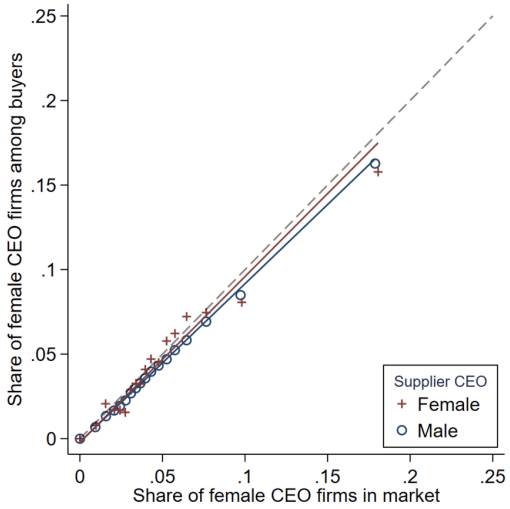
(c) Male CEO



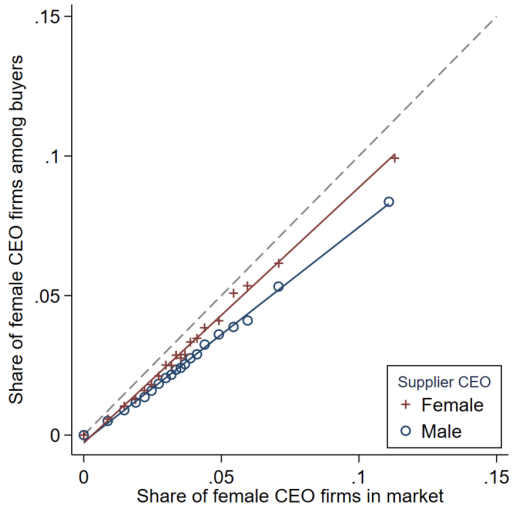
Notes: This figure shows the CEO's involvement in transactions by firm size (small vs medium vs large firms). Panel (a) includes all CEOs, while panels (b) and (c) display the same figure by CEO gender. See Appendix Table A4 for the definition of the firm-size categories. The sample is derived from our original survey, and the level of observation is the respondent CEO of the survey.

Figure 6: Relative Homophily by Firm Size of Suppliers

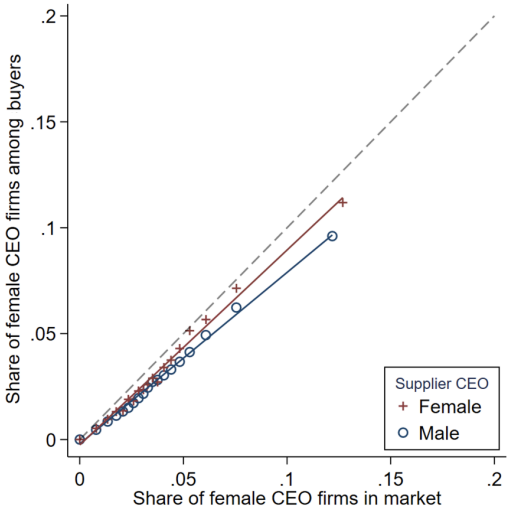
(a) Large firms



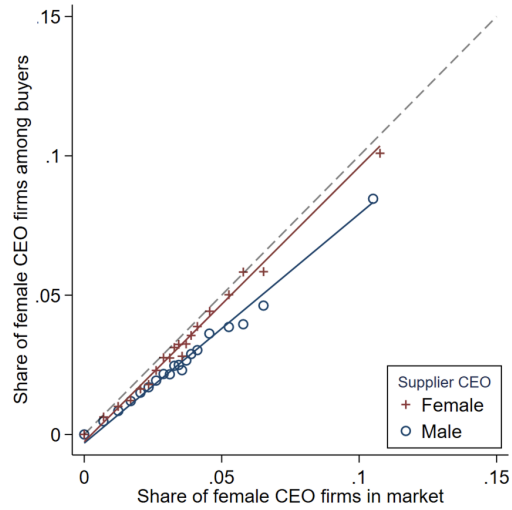
(b) SMEs



(c) Medium-sized firms

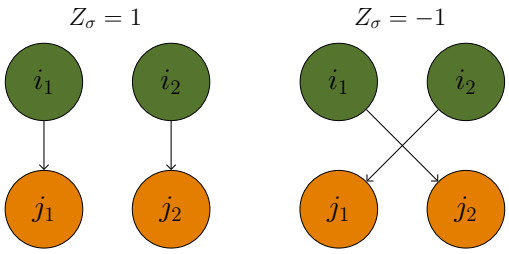


(d) Small-sized firms



Notes: This figure displays a binned scatterplot of the share of female CEO buyers in the market, λ_F^k, on the horizontal axis and the share of transactions with female CEO buyers and female CEO and male CEO suppliers in the market, $T_{g,F}^k$ where $g \in \{f, m\}$, on the vertical axis, along with regression linear lines weighted by market size. Markets are defined as two-digit industry pairs and years. Bins are defined such that the number of observations in each bin is the same. The 45° dotted line indicates the random match. Panel (a) presents the result for large firms, while panel (b) presents the same plot for SMEs. Panels (c) and (d) present the results for medium-sized and small-sized firms, respectively. See Appendix Table A4 for the definition of the firm-size categories.

Figure 7: Sample construction

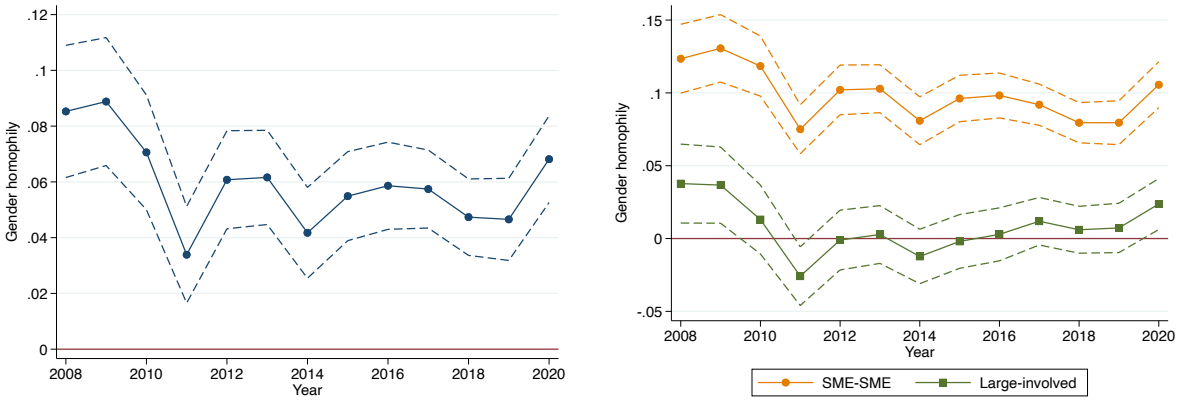


Notes: This figure shows a quadruple of firms, $\{i_1, i_2; j_1, j_2\}$, where $i_1, i_2 \in S_k$, $j_1, j_2 \in B_k$, and Z_σ takes on values from the set $\{-1, 1\}$.

Figure 8: Logit Estimates of Gender Homophily over Time

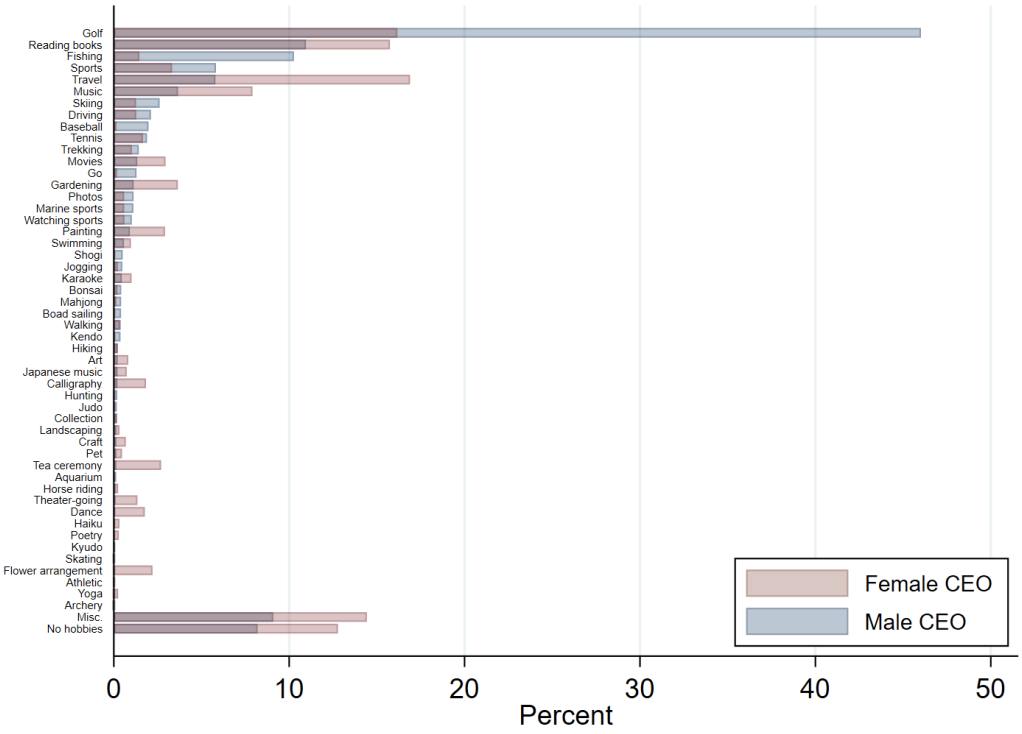
(a) All firms

(b) SME-SME vs. Large-involved



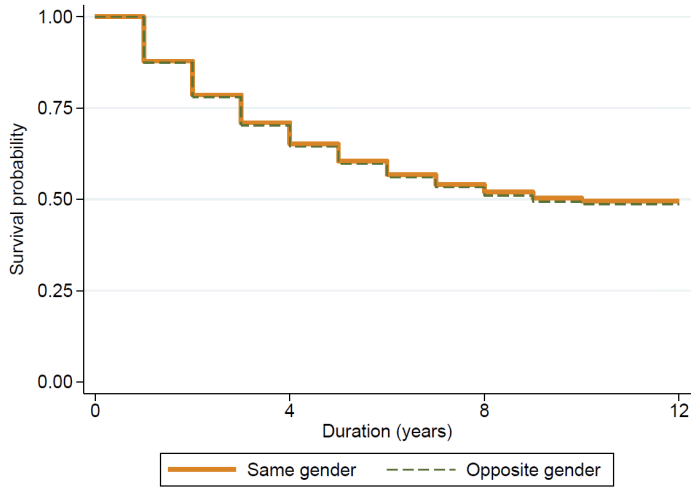
Notes: Panel (a) reports the estimates from equation (1) for all firms, from 2008 to 2020, along with the 95% confidence interval in dotted lines. Each estimate comes from a separate regression. Panel (b) reports the estimates from the variant of equation (1) that further include the interaction of a CEO same-gender dummy and a dummy for firm size category, for SME and large-sized firms involved, from 2008 to 2020, along with the 95% confidence interval in dotted lines.

Figure 9: CEO Hobbies by Gender



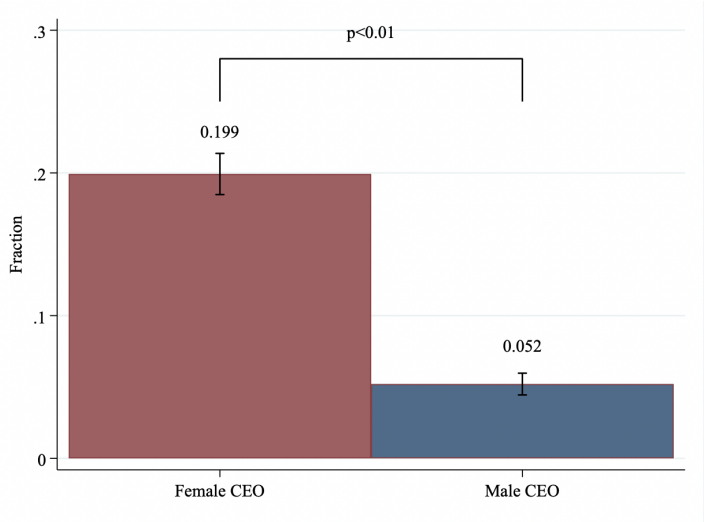
Note: This figure presents the distribution of CEOs' hobbies by gender of CEO. The sample is derived from the TSR data for the period 2008 to 2020. Each CEO provides up to three hobbies. The figure represents the distribution of all reported hobbies; thus, the sum for each gender exceeds 100%.

Figure 10: Kaplan-Meier Curve of Firm-to-Firm Transaction Durations



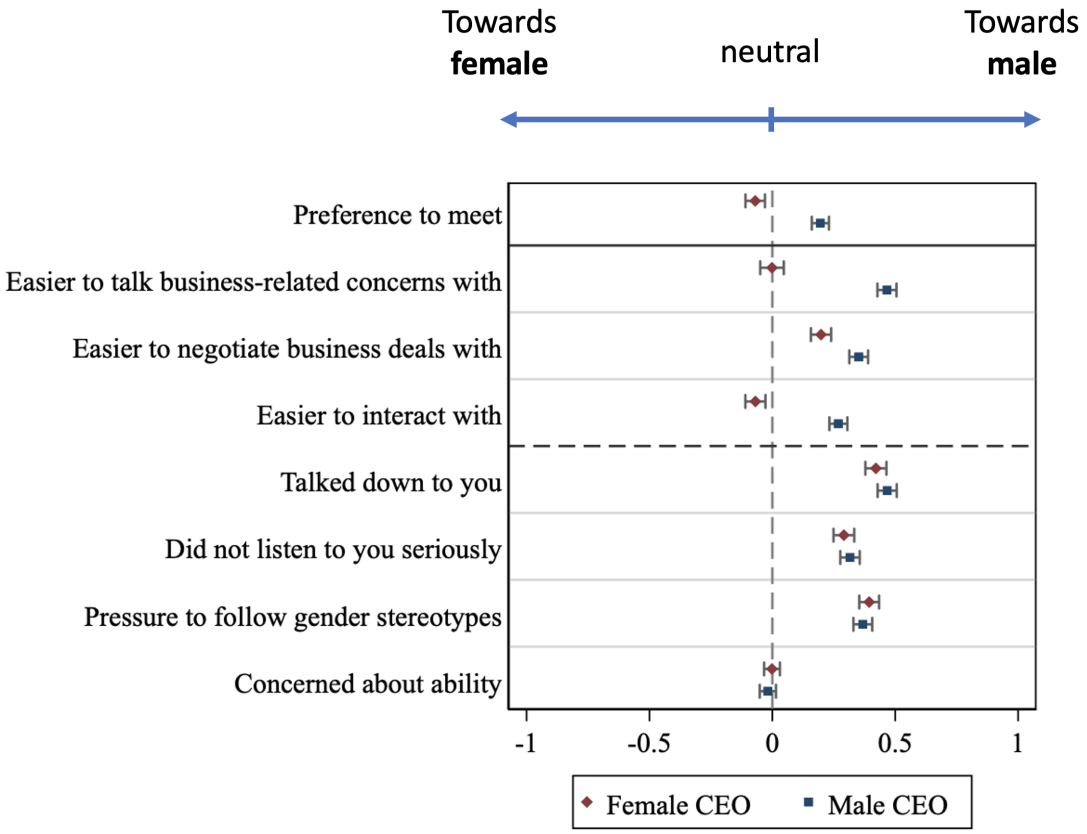
Notes: The figure shows the Kaplan-Meier curves of firm-to-firm transaction durations. The solid line represents supplier-buyer pairs where the CEOs are of the same gender, while the dashed line represents pairs where the CEOs are of opposite genders.

Figure 11: Survey: Gender Differences in Meeting Female CEOs



Notes: The figure above shows the proportion that the CEO with whom the respondent became recently acquainted with is female by respondent gender. The sample is derived from our original survey, and the level of observation is the respondent CEO of the survey. The actual wording of the question is, "Please think of one CEO with whom you have been acquainted with most recently. Please indicate the gender of that person." The responses are 'female,' 'male,' and 'other gender.' The proportion of female CEOs who responded 'female' is 19.9%, and that of male CEOs who responded 'female' is 5.2%.

Figure 12: Survey: Responses of Preference-related Questions



Notes: The figure above shows the results of preference-related questions for CEO gender from our original survey, and the level of observation is the respondent CEO of the survey.
The actual wording of the questions are

- If you could become acquainted with a new CEO, would you like to get to know a male or female CEO, or it does not matter?: responses 'female,' 'male,' and 'neutral.'
- We would like to ask you a few questions about your impressions during interactions and business meetings with CEOs (and other business partners) of other companies. For each of the following, which of the following do you think is more likely to be true of men or women? "easier to talk business-related concerns with," "easier to negotiate business deals with," "easier to interact with," "talked down to you," "did not listen to you seriously," "pressure to follow gender stereotypes," and "more concerned about the other's task ability.": responses 'female,' 'male,' and 'neutral.'

The figure presents the difference in the share of respondents who select male and female options, where coding assigns a value of one if the respondent selects male, zero if they are neutral, and -1 if the respondent selects female and taking the means. Bars are 95% confidence intervals.

Table 1: Summary Statistics (Firm-Level)

	(1) Female CEO			(2) Male CEO			(3) Female - Male		
	N	Mean	SD	N	Mean	SD	Difference	SE	% from male
Panel A. Firm characteristics									
Ln (sale)	495,112	13.825	1.628	8,164,000	14.320	1.755	-0.495***	0.003	-
Ln(employee)	495,112	1.844	1.152	8,164,000	2.131	1.302	-0.287***	0.002	-
Ln(sale/employee)	495,112	11.764	1.190	8,164,000	12.005	1.112	-0.241***	0.002	-
Firm age	495,112	30.098	16.971	8,164,000	31.224	17.134	-1.126***	0.025	-3.607
Listed	495,112	0.001	0.028	8,164,000	0.005	0.072	-0.004***	0.000	-84.829
Credit score	495,112	46.614	5.336	8,164,000	48.006	5.940	-1.393***	0.009	-2.901
Number of suppliers	495,112	2.547	4.730	8,164,000	4.593	27.810	-2.046***	0.040	-44.539
Number of suppliers | Number of suppliers > 0	397,651	3.173	5.087	6,726,868	5.574	30.548	-2.401***	0.048	-43.078
Number of buyers	495,112	2.378	6.254	8,164,000	4.603	29.001	-2.225***	0.041	-48.344
Number of buyers | Number of buyers > 0	325,554	3.617	7.417	6,128,538	6.132	33.332	-2.515***	0.058	-41.012
Panel B. CEO characteristics									
CEO's age	355,540	62.332	12.126	6,997,292	59.810	11.181	2.522***	0.019	4.216
CEO college graduate	188,123	0.296	0.456	4,701,669	0.485	0.500	-0.189***	0.001	-38.981

Notes: The sample is derived from the TSR data for the period 2008 to 2020. The table provides the summary statistics of selected variables for firm (Panel A) and CEO (Panel B) characteristics, by the CEO gender separately. Columns (1) and (2) provide the number of observations (N), mean, and standard deviations (SD) for female CEOs and male CEOs, respectively. Column (3) shows the difference between female and male CEOs. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.10.

Table 2: Summary Statistics: Characteristics of Buyers from Suppliers' Perspectives

	(1) Female CEO suppliers			(2) Male CEO suppliers			(3) Female - Male		
	N	Mean	SD	N	Mean	SD	Difference	SE	% from male
Panel A. Firm characteristics (buyers)									
Ln(sale)	325,554	17.522	2.693	6,128,538	17.483	2.540	0.039***	0.005	-
Ln(employee)	325,554	4.556	2.124	6,128,538	4.513	2.031	0.043***	0.004	-
Ln(sale/employee)	325,554	12.901	1.032	6,128,538	12.904	0.935	-0.002	0.002	-
Large	325,554	0.381	0.404	6,128,538	0.370	0.383	0.012***	0.001	3.150
Medium	325,554	0.345	0.368	6,128,538	0.351	0.344	-0.006***	0.001	-1.843
Small	325,554	0.274	0.371	6,128,538	0.279	0.351	-0.005***	0.001	-1.855
SME	325,554	0.619	0.404	6,128,538	0.630	0.383	-0.012***	0.001	-1.848
Firm age	325,554	44.510	18.460	6,128,538	45.063	17.350	-0.553***	0.031	-1.227
Listed	325,554	0.164	0.288	6,128,538	0.171	0.279	-0.007***	0.001	-3.916
Credit score	325,554	55.640	7.287	6,128,538	55.714	6.955	-0.074***	0.013	-0.132
Ln(distance)	325,554	3.068	1.625	6,128,538	3.248	1.476	-0.180***	0.003	-
Panel B. CEO characteristics (buyers)									
CEO's age	312,013	60.103	7.447	5,935,420	60.140	6.726	-0.037**	0.012	-0.062
CEO college graduate	286,529	0.691	0.374	5,579,295	0.682	0.353	0.009***	0.001	1.312
Female CEO	325,554	0.038	0.150	6,128,538	0.028	0.116	0.010 ***	0.000	37.524

Notes: The sample is derived from the TSR data for the period 2008 to 2020. The table provides the summary statistics of buyers from suppliers' perspective for firm characteristics (Panel A) and CEO characteristics (Panel B), by the gender of CEO suppliers. Columns (1) and (2) provide the number of observations (N), mean, and standard deviations (SD) for female and male CEO suppliers, respectively. Column (3) shows the difference between female and male CEO suppliers, along with the % change from the mean of male CEO suppliers (except for a few variables that already take the log difference). Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.10.

Table 3: Gender Shares in Firm-to-firm Transactions (Raw Data)

(a) From supplier's perspective

	Buyer gender (%)		
	Female (6.0)	Male (94.0)	All (100)
Supplier gender (%)			
Female (5.4)	3.9%	96.1%	100%
Male (94.6)	3.0%	97.0%	100%

(b) From buyers' perspective

	Buyer gender (%)	
	Female (6.0)	Male (94.0)
Supplier gender (%)		
Female (5.4)	3.7%	2.8%
Male (94.6)	96.3%	97.2%
All (100)	100%	100%

Notes: The sample is derived from the TSR data for the period 2008 to 2020. Panel (a) provides the percentage of buyer gender, by the gender of the suppliers. Panel (b) provides the percentage of supplier gender, by the gender of the buyers.

Table 4: Relative Homophily from Suppliers' Perspective

	(1)	(2)	(3)	(4)
Female CEO	0.107***	0.100***	0.092***	0.086***
	(0.012)	(0.011)	(0.011)	(0.019)
Ln(employment)			0.024***	0.030***
			(0.003)	(0.003)
Firm age/100			0.069***	0.122***
			(0.016)	(0.020)
Listed			0.069***	0.039**
			(0.018)	(0.020)
Credit score			-0.002***	-0.001**
			(0.000)	(0.001)
CEO's age/100				0.031
				(0.027)
CEO college graduate				-0.026***
				(0.006)
Year FE	X	X	X	X
Year × Market FE		X	X	X
Industry FE (4-digit)			X	X
Prefecture FE			X	X
CEO birth prefecture FE				X
Observations	16,101,318	16,100,893	16,100,889	9,886,571
R-squared	0.000	0.004	0.006	0.008

Notes: The sample is derived from the TSR data for the period 2008 to 2020, and the level of observation is firm-market-year. Markets are defined as two-digit industry pairs and years. The dependent variable is $\frac{T^k_{i,F}}{\lambda^k_F}$, where λ^k_F is the share of female-led buyers in the market, and $T^k_{i,F}$ is the share of transactions between female-led buyers and female-led suppliers in the market. The estimates from Equation (4) are reported along with the standard errors clustered at the firm level across markets in parentheses. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.10.

Table 5: Logit Estimates of Gender Homophily

Dependent variable	Trade				
	(1)	(2)	(3)	(4)	(5)
CEO same gender	0.051***	0.039***	0.047***	0.090***	0.096***
	(0.005)	(0.007)	(0.008)	(0.017)	(0.017)
ln(distance)		-0.670***	-0.517***	-0.460***	-0.486***
		(0.003)	(0.003)	(0.003)	(0.003)
Large-involved		1.542***	1.430***	1.293***	1.328***
		(0.016)	(0.016)	(0.016)	(0.017)
Same prefecture			0.666***	0.233***	0.569***
			(0.006)	(0.007)	(0.006)
|Δ firm age|			-0.002***	-0.001***	-0.001***
			(0.000)	(0.000)	(0.000)
|Δ credit score|			0.010***	0.010***	0.010***
			(0.000)	(0.000)	(0.000)
Same listed status			-0.268***	-0.259***	-0.271***
			(0.011)	(0.011)	(0.011)
|Δ CEO age|				-0.003***	
				(0.000)	
CEO same birth prefecture				0.870***	
				(0.006)	
CEO same school				0.010	
				(0.008)	
CEO same family name				0.666***	
				(0.012)	
Supplier FE	X	X	X	X	X
Buyer FE	X	X	X	X	X
Number of quadruples	561,013,040	561,013,040	561,013,040	101,319,181	101,319,181
Number of suppliers	473,472	473,472	473,472	196,616	196,616
Number of buyers	511,120	511,120	511,120	235,497	235,497

Notes: The sample is derived from the TSR data in 2019, and the unit of observation is a quadruple of firms $\{i_1, i_2, j_1, j_2\}$. The estimates from Equation (1) are reported along with the standard errors in parentheses. We draw a 5% random sample of all possible quadruples s.t. $Z_\sigma = 1, -1$. The standard errors in parentheses are clustered at the supplier-level (i_1 and i_2) and buyer-level (j_1 and j_2). Shown estimates are odds ratios, but due to sparsity, estimates close to zero are approximately equal to the percentage increase in probability, that is, around zero, $\beta_h \approx (p_{ij}|SameGender_{ij} = 1)/(p_{ij}|SameGender_{ij} = 0) - 1$. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.10.

Table 6: Logit Estimates of Gender Homophily: Heterogeneity by Firm Size

Dependent variable	Trade		
	(1)	(2)	(3)
CEO same gender	0.047***	0.080***	0.109***
	(0.008)	(0.008)	(0.009)
CEO same gender × Large-involved		-0.072***	
		(0.006)	
CEO same gender × Large/medium-involved			-0.066***
			(0.007)
Baseline control	X	X	X
Supplier FE	X	X	X
Buyer FE	X	X	X
Number of quadruples	561,013,040	561,013,040	561,013,040
Number of suppliers	473,472	473,472	473,472
Number of buyers	511,120	511,120	511,120
P-value		0.396	0.000

Notes: The sample is derived from the TSR data in 2019, and the unit of observation is a quadruple of firms $\{i_1, i_2, j_1, j_2\}$. The estimates from a variant of Equation (1) that further include an interaction term between a dummy for the same CEO gender and a dummy for the large-firms involved in Column (2), and an interaction term between a dummy for the same CEO gender and a dummy for the large or medium firms involved in Column (3) are reported along with the standard errors in parentheses. We draw a 5% random sample of all possible quadruples s.t. $Z_\sigma = 1, -1$. The standard errors in parentheses are clustered at the supplier-level (i_1 and i_2) and buyer-level (j_1 and j_2). Baseline controls include variables in Column (3) of Table 5. Shown estimates are odds ratios, but due to sparsity, estimates close to zero are approximately equal to the percentage increase in probability, e.g., around zero, $\beta_h \approx (p_{ij}|SameGender_{ij} = 1)/(p_{ij}|SameGender_{ij} = 0) - 1$. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.10.

Table 7: Logit Estimates of Gender Homophily: CEO Hobby

Dependent variable	Trade		
	(1)	(2)	(3)
CEO same gender	0.086***	0.084***	0.074**
	(0.031)	(0.031)	(0.030)
CEO same hobbies		0.041***	-0.006
		(0.005)	(0.022)
CEO same gender × CEO same hobbies			0.049**
			(0.022)
Baseline control	X	X	X
Supplier FE	X	X	X
Buyer FE	X	X	X
Number of quadruples	11,952,625	11,952,625	11,952,625
Number of suppliers	100,475	100,475	100,475
Number of buyers	124,937	124,937	124,937

Notes: The sample is derived from the TSR data in 2019, and the unit of observation is a quadruple of firms $\{i_1, i_2, j_1, j_2\}$. The estimates from a variant of Equation (1) that further include a dummy for the same CEO hobbies in Column (2), and an interaction term between a dummy for the same CEO gender and a dummy for the same CEO hobbies in Column (3) are reported along with the standard errors in parentheses. We draw a 5% random sample of all possible quadruples s.t. $Z_\sigma = 1, -1$. The standard errors in parentheses are clustered at the supplier-level (i_1 and i_2) and buyer-level (j_1 and j_2). Baseline controls include variables in Column (3) of Table 5. Shown estimates are odds ratios, but due to sparsity, estimates close to zero are approximately equal to the percentage increase in probability, e.g., around zero, $\beta_h \approx (p_{ij}|SameGender_{ij} = 1)/(p_{ij}|SameGender_{ij} = 0) - 1$. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.10.

Table 8: Survey: Summary Statistics

	(1) Female CEO			(2) Male CEO			(3) Female - Male	
	N	Mean	SD	N	Mean	SD	Difference	SE
Panel A. Firm characteristics								
Ln(sale)	3,082	13.616	1.840	3,355	14.127	1.665	-0.512***	0.044
Ln(employment)	3,082	2.064	0.989	3,355	2.233	1.064	-0.169***	0.026
Ln(sale/employment)	3,082	11.552	1.459	3,355	11.894	1.093	-0.342***	0.032
Firm age	3,082	33.611	19.083	3,355	35.147	18.959	-1.536**	0.475
Listed	3,082	0.000	0.000	3,355	0.001	0.039	-0.001*	0.001
Credit score	3,082	46.512	5.333	3,355	47.887	5.747	-1.376***	0.139
Panel B. CEO characteristics								
CEO's age	2,947	61.964	12.960	3,290	61.822	12.714	0.142	0.325
CEO college graduate	2,855	0.473	0.499	3,158	0.509	0.500	-0.037**	0.013
Years of business experience	3,011	24.446	14.454	3,305	28.174	14.755	-3.728***	0.368
Weekly working hour	3,027	40.565	17.077	3,329	45.132	16.341	-4.568***	0.419
Competitiveness: 0 (not competitive)-10 (very competitive)	3,065	6.307	2.206	3,341	6.860	2.108	-0.553***	0.054
Risk attitude: 0 (avoid risk)-10 (seek risk)	3,049	5.629	2.297	3,340	5.917	2.276	-0.289***	0.057
General confidence: 1 (not confident)-7 (very confident)	3,068	4.023	1.381	3,341	4.541	1.271	-0.517***	0.033

Notes: The sample is derived from our original CEO survey. The table provides the summary statistics of selected variables for firm (Panel A) and CEO (Panel B) characteristics, by the gender of CEO respondents separately. Columns (1) and (2) provide the number of observations (N), mean, and standard deviations (SD) for female and male CEOs, respectively. Column (3) shows the difference between female and male CEOs. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.10.

Table 9: Survey: Regressions of Meeting with Female CEOs

Dependent variable	Most recently acquainted CEO is female (dummy)				
	(1)	(2)	(3)	(4)	(5)
Female CEO	0.138***	0.087***	0.076***	0.074***	0.077***
	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)
Survey dummy	X	X	X	X	X
Response to preference-related questions		X	X	X	X
Industry FE and prefecture FE			X	X	X
Firm characteristics				X	X
CEO characteristics					X
Observations	5216	5216	5216	5216	5216
R^2	0.048	0.088	0.119	0.121	0.124

Notes: The sample is derived from our original CEO survey, and the level of observation is the CEO respondent of the survey. The dependent variable is the dummy variable indicating the CEO with whom the respondent became recently acquainted is female. For responses to preference-related questions, we include all the dummies of responses to questions listed in Figure 12. Industry FE is defined as the two-digit industry, and prefecture FE is defined as the prefecture level. Firm characteristics include a log of employment, firm age, listed status, and credit score. CEO characteristics include CEO college graduates, years of business experience, hours of working per week, and psychological attributes, namely competitiveness, risk attitude, and confidence. The standard errors are clustered at the prefecture level. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.10.

Table 10: Counterfactual Simulation

	(1)		(2)		(3)	
	Male CEO		Female CEO		Male - Female	
(A) Raw data	6.03		3.61		2.42	
(B) Baseline prediction	5.92		3.43		2.49	
(C) Counterfactual 1: No gender homophily	5.93	(+0.22%)	3.64	(+6.00%)	2.30	(−7.76%)
(D) Counterfactual 2: Equal gender ratio	5.66	(−3.49%)	3.47	(+1.22%)	2.24	(−9.99%)

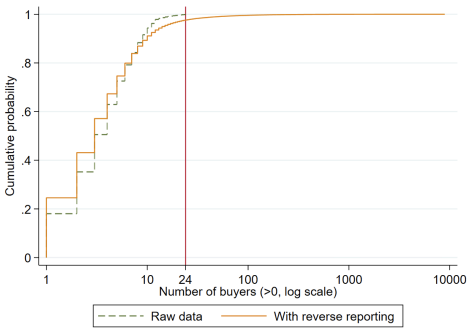
Notes: This table reports the average number of buyers per firm for male-CEO firms (Column 1), female-CEO firms (Column 2), and the difference between them (Column 3). Row (A) presents the figures based on the raw data. Row (B) presents the predicted values from the logit model. Row (C) shows the predicted values under a counterfactual scenario with no gender homophily. Row (D) shows the predicted values under a counterfactual scenario where the CEO gender ratio is equalized. In (D), we report the average number of buyers per firm only for firms whose CEO retained the original gender. The numbers in parentheses are the percentage change from the baseline prediction. The sample is derived from the TSR data in 2019. See Appendix B.3 for further details on the counterfactual simulation.

Online Appendix (not for publication)

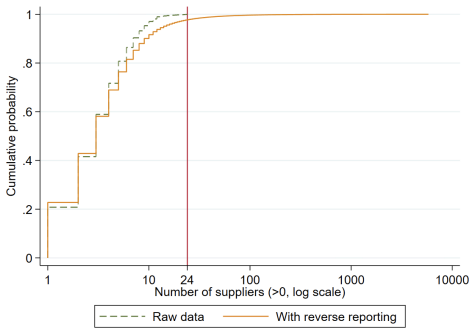
A Additional figures and tables

Figure A1: Distribution of the Number of Suppliers and Buyers

(a) Number of buyers



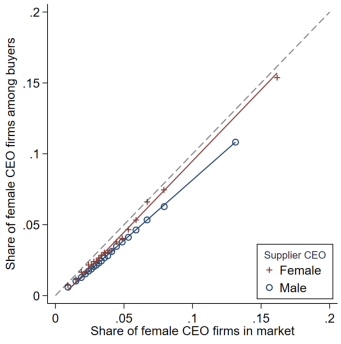
(b) Number of suppliers



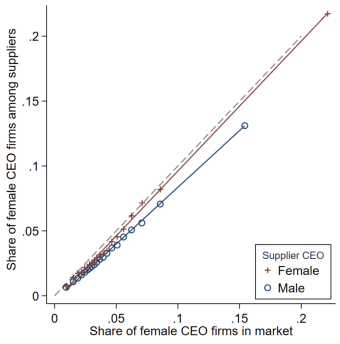
Notes: The figures show the cumulative distribution functions of the number of buyers (Panel a) and suppliers (Panel b) of the firms in our sample for 2008 - 2020. The sample is restricted to firms with at least one buyer (Panel a) and firms with at least one supplier (Panel b).

Figure A2: Relative homophily -Supplier-

(a) 3-digit industry



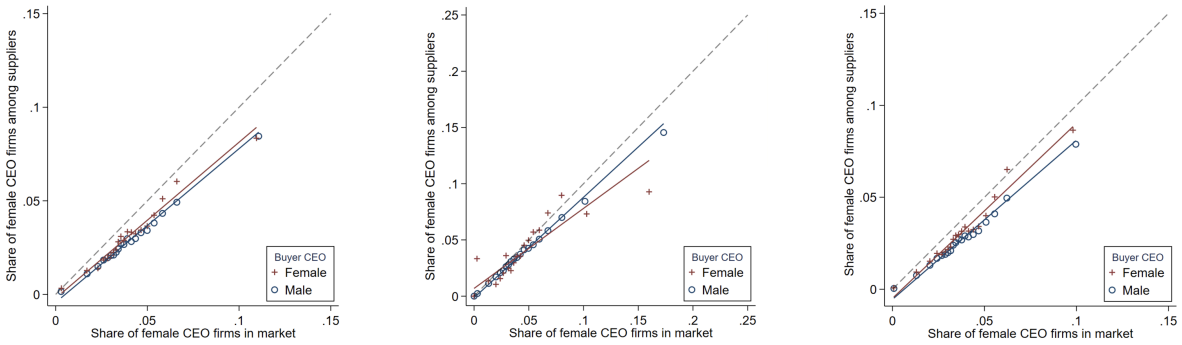
(b) 4-digit industry



Notes: This figure displays a binned scatterplot of the share of female-CEO buyers in the market, λ_F^k, on the horizontal axis and the share of transactions with female-CEO buyers and female-CEO and male-CEO suppliers in the market, $T_{g,F}^k$ where $g \in \{f, m\}$, on the vertical axis, along with regression linear lines weighted by market size. Bins are defined so that the number of observations in each bin is the same. The 45° dotted lines indicate the random match. Markets are defined as three-digit industry pairs and years in Panel (a) and four-digit industry pairs and years in Panel (b). We restrict the sample to the markets with at least one female-CEO firm on each side of the market. See Appendix Table A4 for the definition of the firm-size categories.

Figure A4: Relative homophily -Buyer-

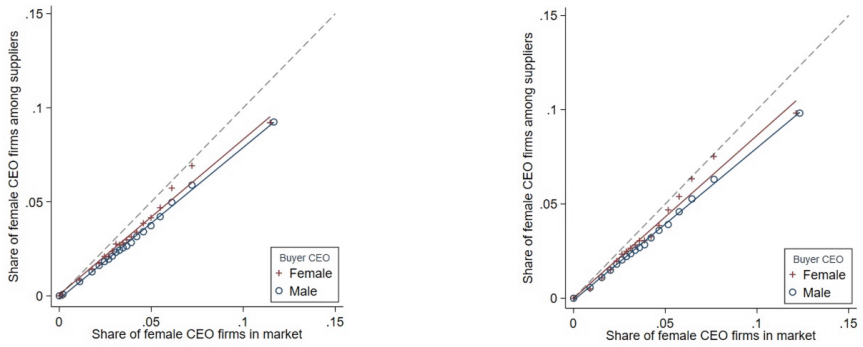
(a) All firms (b) Large firms (c) SMEs



Notes: This figure displays a binned scatterplot of the share of the female-CEO suppliers in the market, λ_f^k, on the horizontal axis and the share of transactions with female-CEO suppliers and female-CEO and male-CEO buyers in the market, $T_{f,g}^k$ where $g \in \{f, m\}$, on the vertical axis, along with regression linear lines weighted by market size. Markets are defined as two-digit industry pairs and years. Markets are defined as two-digit industry pairs and years. Bins are defined such that the number of observations in each bin is the same. The 45° dotted lines indicate the random match. Panels (a), (b), and (c) present the result for all firms, large-sized firms, and SMEs, respectively. See Appendix Table A4 for the definition of the firm-size categories.

Figure A5: Relative homophily -Buyer-

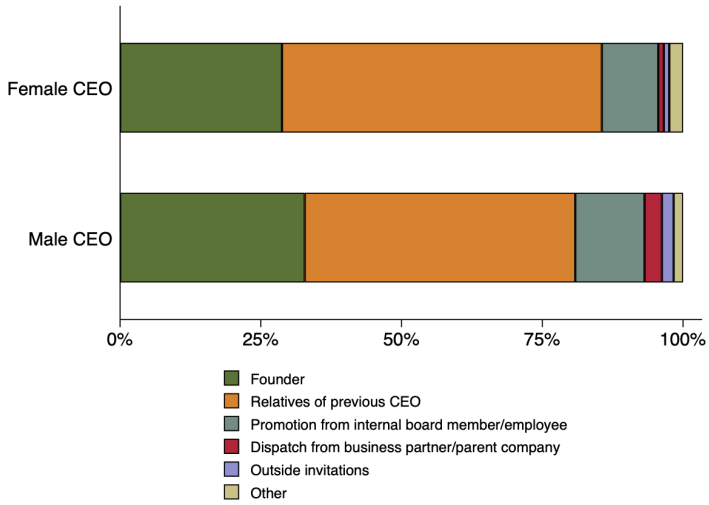
(a) 3-digit industry (b) 4-digit industry



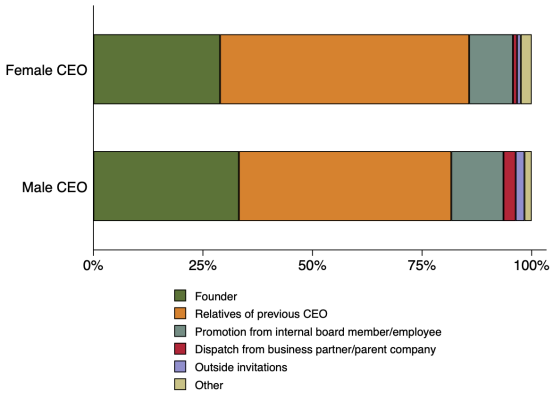
Notes: This figure displays a binned scatterplot of the share of the female-CEO suppliers in the market, λ_f^k, on the horizontal axis and the share of transactions with female-CEO suppliers of female-CEO and male-CEO buyers in the market, $T_{f,g}^k$ where $g \in \{f, m\}$, on the vertical axis, along with regression linear lines weighted by market size. Bins are defined such that the number of observations in each bin is the same. The 45° dotted lines indicate the random match. Markets are defined as three-digit industry pairs and years in Panel (a) and four-digit industry pairs and years in Panel (b).

Figure A6: Background of CEO Appointment by Gender

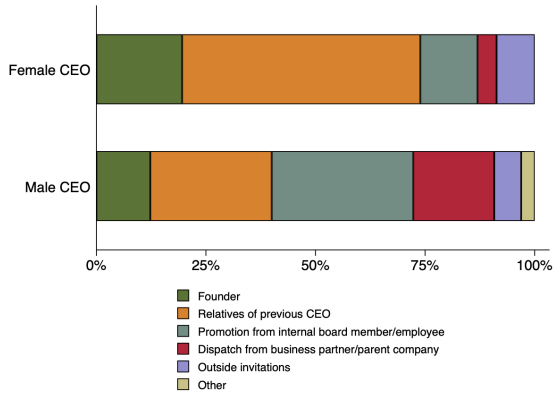
(a) All firms



(b) SMEs



(c) Large firms



Notes: This figure shows the background of CEO appointments by gender. Panel (a) includes all firms, while Panels (b) and (c) display the same figure for SMEs and large firms, respectively. See Appendix Table A4 for the definition of the firm-size categories. The sample is derived from our original survey, and the level of observation is the CEO respondent of the survey.

Table A1: Summary Statistics: Characteristics of Suppliers

	(1) Female CEO buyers			(2) Male CEO buyers			(3) Female - Male		
	N	Mean	SD	N	Mean	SD	Difference	SE	% from male
Panel A. Firm characteristics (suppliers)									
Ln(sale)	397,561	17.343	2.596	6,726,868	17.194	2.465	0.148***	0.004	-
Ln(employee)	397,561	4.270	2.027	6,726,868	4.154	1.906	0.116***	0.003	-
Ln(sale/employee)	397,561	12.999	0.981	6,726,868	12.963	0.928	0.036***	0.002	-
Large	397,561	0.376	0.399	6,726,868	0.357	0.375	0.019***	0.001	5.443
Medium	397,561	0.368	0.377	6,726,868	0.371	0.352	-0.003***	0.001	-0.709
Small	397,561	0.256	0.359	6,726,868	0.273	0.344	-0.017***	0.001	-6.159
SME	397,561	0.624	0.399	6,726,868	0.643	0.375	-0.019***	0.001	-3.017
Firm age	397,561	44.430	17.978	6,726,868	44.289	16.846	0.141***	0.028	0.317
Listed	397,561	0.106	0.237	6,726,868	0.107	0.225	-0.001***	0.000	-1.219
Credit score	397,561	55.287	7.342	6,726,868	55.098	6.895	0.190***	0.011	0.344
Ln(distance)	397,561	3.541	1.610	6,726,868	3.514	1.474	0.026***	0.002	-
Panel B. CEO characteristics (suppliers)									
CEO's age	380,823	59.727	7.650	6,497,967	59.666	7.025	0.061***	0.012	0.102
CEO college graduate	349,059	0.707	0.367	6,055,376	0.698	0.345	0.009***	0.001	1.308
Female CEO	397,561	0.034	0.142	6,726,868	0.026	0.113	0.008***	0.000	30.065

Notes: The sample is derived from the TSR data for the period 2008 to 2020. The table provides the summary statistics of suppliers from buyers' perspective for firm characteristics (Panel A) and CEO characteristics (Panel B), by the gender of CEO buyers'. Columns (1) and (2) provide the number of observations (N), mean, and standard deviations (SD) for female and male CEO buyers, respectively. Column (3) shows the difference between female and male CEO buyers, along with the % change from the mean of male CEO suppliers (except for a few variables which already take the log difference). Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.10.

Table A2: Distribution of Female and Male CEO Firms across Industries

	Industry	Male CEO (%)	Female CEO (%)
A	Agriculture and forestry	0.8	0.7
B	Fisheries	0.1	0.1
C	Mining and quarrying of stone and gravel	0.1	0.1
D	Construction	32.1	24.8
E	Manufacturing	17.1	13.1
F	Electricity, gas, heat supply and water	0.1	0.1
G	Information and communications	2.7	2.3
H	Transport and postal services	3.9	4.0
I	Wholesale and retail trade	24.5	27.4
J	Finance and insurance	0.7	0.8
K	Real estate and goods rental and leasing	3.4	7.1
L	Scientific research, professional and technical services	3.8	3.7
M	Accomodation, eating and drinking services	1.5	3.1
N	Living-related and personal services and amusement services	1.5	3.1
O	Education, learning support	0.4	0.8
P	Medical, health care and welfare	1.8	3.2
Q	Compound services	0.8	0.2
R	Services, N.E.C.	4.6	5.5
	Total	100.0 %	100.0 %

Notes: The sample is derived from the TSR data for the period 2008 to 2020. The industry classification is based on the single-digit Japanese Standard Industry Codes.

Table A3: Share of Female-CEO Firms by Firm Size

	N	Share of female-CEO firms
All	8,659,838	5.7%
Large	298,211	3.4%
Medium	2,651,354	5.0%
Small	5,710,273	6.2%

Notes: The sample is derived from the TSR data for the period 2008 to 2020.

Table A4: Official Definition of Firm Size

	SME (one of two needs to be satisfied)		Small
Industry	Capital stock (Yen)	# of employees	# of employees
Manufacturing, Construction, Transport , and other categories	≤300 million	≤300	≤20
Wholesale trade	≤100 million	≤100	≤5
Service industry	≤50 million	≤100	≤5
Retail trade	≤50 million	≤50	≤5

Note: This definition is based on the provisions of Article 2, Paragraph 1 of the Small and Medium-sized Enterprise Basic Act.

Table A5: Relative Homophily from Buyer's Perspective

	(1)	(2)	(3)	(4)
Female CEO	0.080***	0.111***	0.100***	0.066***
	(0.011)	(0.011)	(0.011)	(0.016)
Ln(employment)			0.041***	0.045***
			(0.002)	(0.002)
Firm age/100			0.012	0.042**
			(0.013)	(0.017)
Listed			-0.016	-0.025
			(0.014)	(0.016)
Credit score			-0.002***	-0.002***
			(0.000)	(0.000)
CEO's age/100				0.032
				(0.024)
CEO college graduate				-0.003
				(0.006)
Year FE	X	X	X	X
Year × Market FE		X	X	X
Industry FE (4-digit)			X	X
Prefecture FE			X	X
CEO birth prefecture FE				X
Observations	19,245,579	19,244,995	19,244,993	12,486,301
R-squared	0.000	0.007	0.009	0.011

Notes: The sample is derived from the TSR data for the period 2008 to 2020, and the level of observation is firm-market-year. Markets are defined as two-digit industry pairs and years. The dependent variable is $\frac{T^k_{i,F}}{\lambda^k_F}$, where λ^k_F is the share of female-led buyers in the market, and $T^k_{i,F}$ is the share of transactions with female-led buyers and female-led suppliers in the market. The estimates from Equation (4) are reported along with the standard errors clustered at the firm level across markets in parentheses. Estimates are weighted by the size of the market. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.10.

Table A6: Relative Homophily from Buyer's Perspective: Heterogeneity by Firm Size

	(1)	(2)	(3)	(4)
Female CEO	0.102***	0.126***	0.103***	0.067***
	(0.011)	(0.011)	(0.011)	(0.017)
Female CEO × large firm	-0.082*	-0.032	-0.072*	-0.012
	(0.043)	(0.042)	(0.044)	(0.058)
Large firm	0.217***	0.184***	0.098***	0.089***
	(0.007)	(0.007)	(0.010)	(0.012)
Ln(employment)			0.030***	0.034***
			(0.002)	(0.003)
Firm age/100			0.019	0.047***
			(0.013)	(0.017)
Listed			-0.044***	-0.052**
			(0.015)	(0.016)
Credit score			-0.002***	-0.002***
			(0.000)	(0.000)
CEO's age/100				0.025
				(0.024)
CEO college graduate				-0.002
				(0.006)
Year FE	X	X	X	X
Year × Market FE		X	X	X
Industry FE (4-digit)			X	X
Prefecture FE			X	X
CEO birth prefecture FE				X
P-value: Female CEO + Female CEO × large = 0	0.622	0.022	0.456	0.320
Observations	19,245,579	19,244,995	19,244,993	12,486,301
R-squared	0.000	0.007	0.009	0.011

Notes: The sample is derived from the TSR data for the period 2008 to 2020, and the level of observation is firm-market-year. Markets are defined as two-digit industry pairs and years. The dependent variable is $\frac{T^k_{i,F}}{\lambda^k_F}$, where λ^k_F is the share of female-led buyers in the market, and $T^k_{i,F}$ is the share of transactions with female-led buyers and female-led suppliers in the market. The estimates from Equation (4) are reported along with the standard errors clustered at the firm level across markets in parentheses. Estimates are weighted by the size of the market. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.10.

Table A7: Logit Estimates of Gender Homophily: Robustness to Alternative Market Definitions

Dependent variable	Trade				
Market definition					
Supplier's industry	2-digit	3-digit	4-digit	3-digit	4-digit
Buyer's industry	2-digit	2-digit	2-digit	3-digit	4-digit
	(1)	(2)	(3)	(4)	(5)
CEO same gender	0.047***	0.051***	0.052***	0.051***	0.045***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)
Baseline control	X	X	X	X	X
Supplier FE	X	X	X	X	X
Buyer FE	X	X	X	X	X
Number of quadruples	561,013,040	201,525,296	132,751,994	85,518,542	47,596,402
Number of suppliers	473,472	467,594	458,948	452,111	418,958
Number of buyers	511,120	506,816	500,435	496,446	467,050

Notes: The sample is derived from the TSR data in 2019, and the unit of observation is a quadruple of firms $\{i_1, i_2, j_1, j_2\}$. The estimates from Equation (1) are reported along with the standard errors in parentheses. We draw a 5% random sample of all possible quadruples s.t. $Z_\sigma = 1, -1$. The standard errors in parentheses are clustered at the supplier-level (i_1 and i_2) and buyer-level (j_1 and j_2). Baseline controls include variables in Column (3) of Table 5. Shown estimates are odds ratios, but due to sparsity, estimates close to zero are approximately equal to the percentage increase in probability, that is, around zero, $\beta_h \approx (p_{ij}|SameGender_{ij} = 1)/(p_{ij}|SameGender_{ij} = 0) - 1$. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.10.

Table A8: Cox Regression Estimation Results

	(1)
CEO same gender	-0.018
	(0.012)
Year FE	X
Firm-level controls	X
Firm pair-level controls	X
Number of observations	2,517,468

Notes: The sample is derived from the TSR data from 2009 to 2020, and the unit of observation is a sequence of trade. Firm-level controls include ln(employment), firm age, listed status, credit score, prefecture fixed effects, and 4-digit industry fixed effects for both the supplier firm and the buyer firm. Firm-pair level controls include ln(distance), a large-involved trade dummy, the absolute value of the difference in firm ages, the absolute value of the difference in credit scores, and the same prefecture dummy. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.10.

Table A9: Survey: Characteristics of Respondents and Non-respondents

	(1) Response			(2) Non-response			(3) Response - Non-response	
	N	Mean	SD	N	Mean	SD	Difference	SE
Panel A. Firm characteristics								
Ln(sale)	6,437	13.882	1.770	18,563	13.922	1.988	-0.040	0.028
Ln(employment)	6,437	1.947	1.186	18,563	1.969	1.333	-0.021	0.019
Ln(sale/employment)	6,437	11.935	1.274	18,563	11.953	1.384	-0.019	0.020
Firm age	6,437	34.411	19.032	18,563	33.397	18.819	1.015***	0.273
Listed	6,437	0.001	0.028	18,563	0.004	0.060	-0.003***	0.001
Credit score	6,437	47.229	5.594	18,563	46.824	5.883	0.404***	0.084
Panel B. CEO characteristics								
Female CEO	6,437	0.479	0.500	18,563	0.507	0.500	-0.029***	0.007

Notes: The sample is derived from our own survey. The table provides the summary statistics of firm characteristics and CEO characteristics, separately by respondents (Column 1) and non-respondents (Column 2). Column 3 presents the difference between respondents and non-respondents.

Table A10: Survey: Responses to Preference Related Questions

	(1) Female CEO			(2) Male CEO		
	N	Mean	SE	N	Mean	SE
Preference to meet	3,058	-0.069***	0.010	3,332	0.195***	0.009
Panel A. Positive Interactions						
Easier to talk business-related concerns with	2,877	-0.001	0.012	3,163	0.466***	0.010
Easier to negotiate business deals with	2,893	0.198***	0.011	3,184	0.351***	0.010
Easier to interact with	2,903	-0.069***	0.011	3,189	0.269***	0.010
Panel B. Negative Interactions						
Talked down to you	2,796	0.421***	0.011	3,097	0.467***	0.010
Did not listen to you seriously	2,768	0.291***	0.011	3,086	0.316***	0.010
Pressured to follow gender stereotypes	2,768	0.394***	0.010	3,064	0.368***	0.010
More concerned about ability	2,825	-0.001	0.008	3,119	-0.019*	0.009

Notes: This table shows the results of preference-related questions for CEO gender from our original survey, and the level of observation is the respondent CEO of the survey. The actual questions are

- If you could become acquainted with a new CEO, would you like to get to know a male CEO, a female CEO, or it does not matter?": responses 'female;' 'male;' 'neutral.'
- We would like to ask you a few questions about your impressions during interactions and business meetings with CEOs (and other business partners) of other companies. For each of the following, which of the following do you think is more likely to be true of men or women? "easier to talk business-related concerns with," "easier to negotiate business deals with," "easier to interact with," "talked down to you," "did not listen to you seriously," "pressure to follow gender stereotypes," and "more concerned about the other's task ability.": responses 'female;' 'male;' 'neutral.'

The table presents the difference in the share of respondents who select male and female options, where coding assigns a value of one if the respondent selects male, zero if they are neutral, and -1 if the respondent selects female and taking the means. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.10.

B Technical appendix

B.1 Proof of the Propositions

Proposition 1. *Given a market $k \in K$ and suppose the market is sufficiently large, then, if $\lambda_F^k > 0$ and (X_i, α_i^k) are independently distributed among the gender of suppliers CEO, $\beta_h > 0$ if and only if $T_{f,F}^k > T_{m,F}^k$.*

Proof. Fix a market $k \in K$ and let us denote $\lambda_F^k \equiv Pr(G_j = F | j \in B^k), \tilde{\alpha}_i \equiv (X_i, \alpha_i^k), \tilde{\gamma}_j \equiv (X_j, \gamma_j^k)$, $\omega(\tilde{\alpha}_i, \tilde{\gamma}_j) \equiv g(X_i, X_j)'\delta + \alpha_i^k + \gamma_j^k$, and $\Lambda(\cdot) \equiv \frac{\exp(\cdot)}{1+\exp(\cdot)}$. Then for $g \in \{f, m\}$,

$$
\begin{aligned}
&T_{g,F}^k \to_p E[Pr(G_j = F | g_i = g, Y_{ij} = 1, j \in B^k, \tilde{\alpha}_i) | i \in S_g^k] \\
&= \int \frac{\lambda_F^k E_{\tilde{\gamma}_j|F,k}[\Lambda(\beta_h \mathbb{I}(g = f) + \omega(\tilde{\alpha}_i, \tilde{\gamma}_j))]}{\lambda_F^k E_{\tilde{\gamma}_j|F,k}[\Lambda(\beta_h \mathbb{I}(g = f) + \omega(\tilde{\alpha}_i, \tilde{\gamma}_j))] + (1 - \lambda_F^k) E_{\tilde{\gamma}_j|M,k}[\Lambda(\beta_h \mathbb{I}(g = m) + f(\tilde{\alpha}_i, \tilde{\gamma}_j))]} f(\tilde{\alpha}_i | i \in S_g^k) d\tilde{\alpha},
\end{aligned}
$$

as the market becomes large. Therefore, calculating the probability limit of $T_{f,F}^k - T_{m,F}^k$ and rewriting the expression, we have

$$
\begin{aligned}
&T_{f,F}^k - T_{m,F}^k \\
&\to_p \int \left\{ \frac{\lambda_F^k E_{\tilde{\gamma}_j|F,k}[\Lambda(\beta_h + \omega(\tilde{\alpha}_i, \tilde{\gamma}_j))]}{\lambda_F^k E_{\tilde{\gamma}_j|F,k}[\Lambda(\beta_h + \omega(\tilde{\alpha}_i, \tilde{\gamma}_j))] + (1 - \lambda_F^k) E_{\tilde{\gamma}_j|M,k}[\Lambda(\omega(\tilde{\alpha}_i, \tilde{\gamma}_j))]} \right. \\
&\qquad \left. - \frac{\lambda_F^k E_{\tilde{\gamma}_j|F,k}[\Lambda(\omega(\tilde{\alpha}_i, \tilde{\gamma}_j))]}{\lambda_F^k E_{\tilde{\gamma}_j|F,k}[\Lambda(\omega(\tilde{\alpha}_i, \tilde{\gamma}_j))] + (1 - \lambda_F^k) E_{\tilde{\gamma}_j|M,k}[\Lambda(\beta_h + \omega(\tilde{\alpha}_i, \tilde{\gamma}_j))]} \right\} f(\tilde{\alpha}_i | i \in S_f^k) d\tilde{\alpha} \\
&\quad + \int \frac{\lambda_F^k E_{\tilde{\gamma}_j|F,k}[\Lambda(\omega(\tilde{\alpha}_i, \tilde{\gamma}_j))]}{\lambda_F^k E_{\tilde{\gamma}_j|F,k}[\Lambda(\omega(\tilde{\alpha}_i, \tilde{\gamma}_j))] + (1 - \lambda_F^k) E_{\tilde{\gamma}_j|M,k}[\Lambda(\beta_h + \omega(\tilde{\alpha}_i, \tilde{\gamma}_j))]} \{ f(\tilde{\alpha}_i | i \in S_m^k) - f(\tilde{\alpha}_i | i \in S_f^k) \} d\tilde{\alpha}.
\end{aligned}
$$

The second term is zero when $\tilde{\alpha}_i$ is independently distributed among the gender of CEO suppliers: i.e., $f(\tilde{\alpha}_i | i \in S_m^k) = f(\tilde{\alpha}_i | i \in S_f^k)$. Furthermore, the first term is equal to zero if and only if $\beta_h = 0$ when $\lambda_{F,k} > 0$. This completes the proof. □

Proposition 2. *If ϵ_{ij} are independent and identically distributed and follow the standard logistic distribution,*

$$
\Pr(Z_\sigma = 1 | R_\sigma, Z_\sigma \in \{-1, 1\}) = \frac{\exp(R_\sigma' \theta)}{1 + \exp(R_\sigma' \theta)},
$$

where $R_\sigma \equiv (W_{i_1 j_1} - W_{i_1 j_2}) - (W_{i_2 j_1} - W_{i_2 j_2})$.

Proof. Fix a market $k \in K$. Let us denote $W_{ij} \equiv (SameGender_{ij}, g(X_i, X_j))'$, $\theta \equiv (\beta_h, \delta)$ and

rewrite the model (1) as

$$Y_{ij} = \mathbb{I}\{W_{ij}'\theta + \alpha_i^k + \gamma_j^k - \epsilon_{ij} \geq 0\},$$

where α_i^k and γ_j^k are supplier and buyer fixed effects. ϵ_{ij} is an unobserved idiosyncratic component that follows the logistic distribution independent from i and j. Fix a quadruple of distinct firms $\sigma^k \equiv \{i_1, i_2; j_1, j_2\}$, where $i_1, i_2 \in S^k$ and $j_1, j_2 \in B^k$, and define the random variable

$$Z_\sigma \equiv \frac{(Y_{i_1j_1} - Y_{i_1j_2}) - (Y_{i_2j_1} - Y_{i_2j_2})}{2},$$

and collect $W_\sigma \equiv (W_{i_1j_1}, W_{i_1j_2}, W_{i_2j_1}, W_{i_2j_2})$. Note that Z_σ can take on values from the set $\{-1, -1/2, 0, 1/2, 1\}$. Conditional on W_σ and the event $Z_\sigma \in \{-1, 1\}$,

$$\Pr(Z_\sigma = 1|W_\sigma, Z_\sigma \in \{-1,1\}) = \frac{\Pr(Z_\sigma = 1|W_\sigma)}{\Pr(Z_\sigma = -1|W_\sigma) + \Pr(Z_\sigma = 1|W_\sigma)},$$

where

$$\begin{aligned}
\Pr(Z_\sigma = 1|W_\sigma) &= \Pr(Y_{i_1j_1} = 1|W_\sigma)\Pr(Y_{i_1j_2} = 0|W_\sigma)\Pr(Y_{i_2j_1} = 0|W_\sigma)\Pr(Y_{i_2j_2} = 1|W_\sigma) \\
&= \frac{\exp(W_{i_1j_1}'\theta + \alpha_{i_1}^k + \gamma_{j_1}^k)}{1 + \exp(W_{i_1j_1}'\theta + \alpha_{i_1}^k + \gamma_{j_1}^k)} \frac{1}{1 + \exp(W_{i_1j_2}'\theta + \alpha_{i_1}^k + \gamma_{j_2}^k)} \\
&\times \frac{1}{1 + \exp(W_{i_2j_1}'\theta + \alpha_{i_2}^k + \gamma_{j_1}^k)} \frac{\exp(W_{i_2j_2}'\theta + \alpha_{i_2}^k + \gamma_{j_2}^k)}{1 + \exp(W_{i_2j_2}'\theta + \alpha_{i_2}^k + \gamma_{j_2}^k)},
\end{aligned}$$

and

$$\begin{aligned}
\Pr(Z_\sigma = -1|W_\sigma) &= \Pr(Y_{i_1j_1} = 0|W_\sigma)\Pr(Y_{i_1j_2} = 1|W_\sigma)\Pr(Y_{i_2j_1} = 1|W_\sigma)\Pr(Y_{i_2j_2} = 0|W_\sigma) \\
&= \frac{1}{1 + \exp(W_{i_1j_1}'\theta + \alpha_{i_1}^k + \gamma_{j_1}^k)} \frac{\exp(W_{i_1j_2}'\theta + \alpha_{i_1}^k + \gamma_{j_2}^k)}{1 + \exp(W_{i_1j_2}'\theta + \alpha_{i_1}^k + \gamma_{j_2}^k)} \\
&\times \frac{\exp(W_{i_2j_1}'\theta + \alpha_{i_2}^k + \gamma_{j_1}^k)}{1 + \exp(W_{i_2j_1}'\theta + \alpha_{i_2}^k + \gamma_{j_1}^k)} \frac{1}{1 + \exp(W_{i_2j_2}'\theta + \alpha_{i_2}^k + \gamma_{j_2}^k)}.
\end{aligned}$$

Thus,

$$\Pr(Z_\sigma = 1|W_\sigma, Z_\sigma \in \{-1,1\}) = \frac{\exp(((W_{i_1j_1} - W_{i_1j_2}) - (W_{i_2j_1} - W_{i_2j_2}))'\theta)}{1 + \exp(((W_{i_1j_1} - W_{i_1j_2}) - (W_{i_2j_1} - W_{i_2j_2}))'\theta)},$$

which is the desired form. □

B.2 Interpretation of the Logit Estimates under Sparsity

Let ξ_{ij} be all factors other than $SameGender_{ij}$ in the model. Note that,

$$\Pr(Y_{ij}=1|SameGender_{ij}=1,\xi_{ij})=\frac{\exp(\beta_h+\xi_{ij})}{1+\exp(\beta_h+\xi_{ij})}$$
$$\Pr(Y_{ij}=1|SameGender_{ij}=0,\xi_{ij})=\frac{\exp(\xi_{ij})}{1+\exp(\xi_{ij})}.$$

Taking the ratio, we have

$$\frac{\Pr(Y_{ij}=1|SameGender_{ij}=1,\xi_{ij})}{\Pr(Y_{ij}=1|SameGender_{ij}=0,\xi_{ij})}=\exp(\beta_h)\frac{1+\exp(\xi_{ij})}{1+\exp(\beta_h+\xi_{ij})}.$$

Note that, under sparsity and β_h close to zero, the right-hand side is approximately equal to $\exp(\beta_h)\approx 1+\beta$. Therefore,

$$\frac{\Pr(Y_{ij}=1|SameGender_{ij}=1,\xi_{ij})}{\Pr(Y_{ij}=1|SameGender_{ij}=0,\xi_{ij})}-1\approx\beta_h,$$

where the left-hand side is the percentage increase in probability divided by 100.

B.3 Counterfactual Exercises

Here, we provide details on the counterfactual analysis in Table 10. Let $Q^k_{g,G}$ be the number of transacting pairs in market k with the CEO gender of the suppliers and buyers being $g\in\{f,m\}$ and $G\in\{F,M\}$ as in the main text. Assume that market k is sufficiently large. Then note that,

$$\begin{aligned}Q^k_{g,G}=&|S^k_g||B^k_G|\frac{Q^k_{g,G}}{|S^k_g||B^k_G|}\\ \approx&|S^k_g||B^k_G|\Pr(Y_{ij}=1|i\in S^k_g,j\in B^k_G),\end{aligned}$$

where the last approximation follows the assumption that the market size is sufficiently large. To evaluate the impact of eliminating the effect of gender homophily on the probability of transaction occurrence, note that the logit link formation Model (1) implies,

$$\begin{aligned}&\Pr(Y_{ij}=1|i\in S^k_g,j\in B^k_G)\\ =&E\left[\frac{\exp(\beta_h\times SameGender_{ij}+g(X_i,X_j)'\delta+\alpha^k_i+\gamma^k_j)}{1+\exp(\beta_h\times SameGender_{ij}+g(X_i,X_j)'\delta+\alpha^k_i+\gamma^k_j)}\middle| i\in S^k_g,j\in B^k_G\right].\end{aligned}$$

Therefore, we assess the extent to which the above probability of transactions between CEOs of different genders would be affected when they can enjoy the same merit of β_h as transactions between CEOs of the same gender. The problem here is that in our previous analysis, although

we estimated the coefficients β_h and δ for pair-level variables, the unobserved heterogeneity α_i^k and γ_j^k were differenced out during the estimation process, making it impossible to compute predicted probabilities for each pair (i, j) inside the expectation. To address this problem, we proceed by linearly specifying $\alpha_i^k = Z_i'\tilde{\alpha}^k$ and $\gamma_j^k = Z_j'\tilde{\gamma}^k$ using the observed variables Z_i and Z_j. We then estimate $\tilde{\alpha}^k$ and $\tilde{\gamma}^k$ through standard logit estimation, thereby *fixing* the previously estimated values of β_h and δ.[30] For Z_i and Z_j, we include a female CEO dummy, firm age, log of the number of employees, credit score, listed dummy, two-digit industry, and prefecture fixed effects.

In estimating $\tilde{\alpha}^k$ and $\tilde{\gamma}^k$, we use supplier-buyer dyad data, which is constructed using choice-based sampling. Specifically, for each market k, we randomly sample non-trading supply-buyer pairs within the market and construct weights using the inverse of the sampling probability. Importantly, when sampling non-trading pairs, we further stratify cells of non-trading pairs based on CEO gender pairs $(M-m, M-f, F-m, F-f)$ to ensure that rare pairs such as female-to-female are well-represented in the sample.

Row (A) of Table 10 displays the average number of transactions per supplier with buyers based on actual data.[31] Row (B) represents the average number of transactions per supplier with buyers predicted by the estimated model. The discrepancies between the actual and predicted numbers of transactions are all below 5%, indicating that the predicted probabilities of transactions match the actual probabilities pretty well. Row (C) shows the counterfactual results for the number of transactions per supplier with buyers assuming the absence of gender homophily, meaning that there is an equal likelihood of transactions occurring between different-gender CEOs and same-gender CEOs.

Finally, in Row (D), we simulate how the business environment would change if the CEO gender ratio in the market became 50-50, while keeping firm characteristics constant. In this counterfactual scenario, we examine the average number of transactions per supplier only for firms retaining the original CEO gender to isolate the impact of a more gender-balanced market composition, holding firm-level traits fixed. We proceed as follows:

1. Randomly reassign CEO gender labels across all firms in the sample such that the overall gender ratio becomes 50-50.

2. Predict the number of transactions based on the randomly assigned CEO gender, using the estimated model.

3. Identify firms for which the randomly assigned gender matches the CEO's actual gender and calculate the number of transactions for them. Note that, because the reassignment

[30] Note that the purpose here is not to *consistently* estimate the true parameters but to *fit* the model such that the predicted transaction probability approximately matches the observed data.

[31] Using notations above, we calculate $\sum_k (Q_{g,F}^k + Q_{g,M}^k)/|S_g|$ for each suppliers gender $g \in \{m, f\}$ where $|S_g| = |\cup_k S_g^k|$ in Columns (1) and (2), and $\sum_k (Q_{m,F}^k + Q_{m,M}^k)/|S_m| - \sum_k (Q_{f,F}^k + Q_{f,M}^k)/|S_f|$ in Column (3).

is random, this subset of "matched" firms retains the same distribution of firm characteristics (e.g., size, industry) across female- and male-led firms as in the real data. This ensures comparability across groups.