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Networking: a business for women

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Abstract This paper uses firm-level data and Data Envelopment Analysis (DEA) methods to investigate the effects of participation in formal networking activities and of female representation in leadership positions on firm's economic efficiency. Our findings show that firms belonging to a network have a higher level of technical efficiency (i.e., the position of network members is closer to the technical efficient frontier), while the presence of women in senior roles (CEO, president, or member of the board of directors) is associated to lower efficiency scores. However, the observed performance strongly increases when firms with women in top positions participate to networks, hinting at superior returns for female networking. This interaction effect is found to be stronger in female-intensive working environments and networks, as well as in innovative and digital intensive sectors.

Keywords Firm networks · Female leaders · Technical efficiency · Data envelopment analysis

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1 Introduction

A growing strand of the economic literature considers the effect of firms' networking activities and cooperation on firms' performance. A general consensus is emerging that supports the existence of positive economic and financial effects from being member of networks, suggesting that cooperating with peers is an important source of competitive advantage (Dyer and Singh 1998). This advantage materializes mainly through two mechanisms: a low-cost access to knowledge or resources (Gulati and Higgins 2003; Zaheer and Bell 2005) and the possibility to reach the benefits of scale-economies without increasing the firm's size (Watson 2007). While many papers show a general positive effect from networking on different measures of economic or financial performance, for instance profitability (Watson 2007) or penetration in foreign markets (Cisi et al. 2016), less attention has been devoted to long-term oriented or more specific definitions of performance, such as total factor productivity or technical efficiency.

Another emerging, but separate, literature is concerned with the general effects stemming from an increase in female participation to leadership positions within firms. The empirical literature in this case is still far from converging towards a consensus on the impact on performance of having more women among top managers and in the board of directors, even if such an increase may have socially and culturally desirable implications. The results are still mixed: While some contributions find modest positive effects (Green and Homroy 2018; Dezso and Ross 2012; Flabbi et al. 2019), other studies show no effects (Comi et al. 2017; Ferrari et al. 2016; Gregory-Smith et al. 2013), or even point towards the presence of a negative impact (Matsa and Miller 2013; Ahern and Dittmar 2012; Adams and Ferreira 2009) of an increase of female representation in senior positions on performance. Such a high heterogeneity of results depends also on the inclusion or omission of explanatory variables such as the share of female employees or the share of women at lower levels of management. Within these works, we observe a significant prevalence of contributions focused on large and very large or listed firms, while small and medium firms (SMEs) often are under-represented, despite their importance in many economies, especially in Southern European Countries. Clearly, more work is needed in both literatures. More importantly, there appears to be a large scope for new insights by combining elements of the two literatures, which have developed separately, so far. In this respect, some recent experimental results provided by Kuhn and Villeval (2015) highlight a greater capacity of women to cooperate and to create successful teams as compared to men. This idea stimulates new interest in investigating the contribution of female leaders to cooperation among firms. If women engage in networking activities in different ways than men, a question naturally arises as to whether female leaders are able to bring firm-wide benefits through the creation of more effective and incisive networks among firms, as compared to men leaders.

Our paper contributes to the above debate in several ways. First, we introduce a precise and long-term oriented definition of firm performance based on global productivity measures: In particular, we adopt a classical technical efficiency framework based on linear programming (i.e., Data Envelopment Analysis). According to this, we are able to estimate efficiency scores reflecting, for each firm in the sample, the capacity of combining inputs and outputs in comparison to a flexible best available frontier, defined without assuming any functional form for the underlying technology, which is common for all firms within the same sector. While the use of such a measure of performance is essentially new in the literature on firms' networks, it can add value with respect to classical measures of performance (such as ROA or ROE), since through networking firms can increase the ability to share the "best" technology. Second, we adopt a clear and established notion of networking, by focusing on firms that signed a legal agreement labeled "network contract." Our network members are therefore engaged in a strong form of formalized cooperation, in line with the classical definition given by Parker (2008)[1] or Huggins (2001)[2] and recently confirmed by Huggins and Thompson (2015). Third, we investigate how the obtained indicators (scores) of technical efficiency are affected by female representation in top positions and by the firm's participation in networks. In particular, we also explore the existence of any interaction with the digitalization process (i.e., the degree of participation to the so-called fourth industrial revolution or Industry 4.0) that we measure at the sector level according to some recent classifications proposed at the OECD level by Calvino et al. (2018).

We base our econometric analysis on a database obtained by merging two different data sources: first, economic and financial data for all the Italian firms operating in the manufacturing sector and, second, information on firm's participation to formal networks, on the presence of female leaders within each firm, as well as within each of its partners in the network.

Our findings show that, in general, network members have a higher level of technical efficiency (i.e., networking firms are closer to the technical efficient frontier), while the presence of women in senior positions is found to reduce the estimated efficiency scores. However, when firms with female leaders participate to networks, the observed performance strongly increases. The higher firm-wide returns to female networking are even larger in female-intensive working environments and networks, and in high-tech and digital intensive industries.

The remainder of the paper is organized as follows: The next section reviews the literature on networking, female participation in leading positions and performance. Section 3 presents the methodology adopted, while Section 4 describes our database, sample selection, and the variables used. Section 5 presents and discusses our main results, and Section 6 briefly concludes.

[1] According to Parker (2008), a business network is a group of entrepreneurs that voluntarily decide to share knowledge and experiences.

[2] Huggins (2001) defines formal networks as group of firms that voluntarily cooperate with the explicit aim of co-producing, co-marketing, co-purchasing, or co-operating in product or market development. This definition reflects the specific contractual scheme, named *network contract*, recently introduced in Italy and object of this study. See Appendix for additional details.

2 Conceptual framework and relevant literature

2.1 Networks and performance

The theoretical literature has long highlighted that belonging to a network might be beneficial for a firm's performance, through a number of mechanisms. Networks facilitate knowledge flows or technological improvements (Vanhaverbeke et al. 2009), contribute to contain transaction costs (Lin and Lin 2016), and provide a source of flexible and relatively cheap resources for all members, also stimulating product and process innovation (Schott and Jensen 2016; Mazzola et al. 2016). The empirical literature seems to confirm the theoretical predictions on the positive effects of networking, although the available results are often not easily comparable across studies, because of a number of issues, such as the specific definition of a network, the kinds of firms analyzed, and the methodological approaches adopted by the different authors (Schoonjans et al. 2013). A first complication derives from the difficulty in disentangling the effect of networking from a range of other concomitant activities, which might have independent impacts on a firm's performance. For instance, Schoonjans et al. (2013) report a positive and significant effect of networking on net asset growth and on value-added growth for East-Flanders SMEs during the period 1992–2008. However, their networks are identified according to the participation to a specific government program aimed at favoring contacts and experiences exchanges among managers of SMEs, also through training sessions, so it is not clear if the effect is due to networking per se or to the training program. Another problematic aspect is how to properly define a network: Networking is often a self-reported activity that may refer to very different kinds of interactions and to different levels of cooperation, spanning from those that are quite informal in nature, to those formalized through specific contractual agreements. For instance, Watson (2011) uses survey data on Australian firms in the period 1994–1997 and finds evidence of positive effects of networking on firms' survival and growth, albeit only for some specific types of formal networks (i.e., business consultants).[3] Similarly, Park et al. (2010) find that networking has a positive effect on sales growth and survival of manufacturing firms operating in Korea in the period 1994–2003, where networking coincides with the presence of industrial clusters. Additionally, while some studies focus on SMEs, others restrict attention to large firms, for which the results are less clear cut and vary from the positive effects on profits found by Ritala (2012) for Swedish firms to the negative effects reported Koka and Prescott (2008) for periods of radical changes in the international steel industry. Finally, the various papers adopt different proxies for performance (profitability, productivity, exports, or innovation activities) as well as different methodologies to estimate the impact of networking on firm performance.

Our paper contributes to the existing literature by taking a specific stance on each of the aspects identified above. We focus on Italian manufacturing firms, mainly SMEs, as networking is often a key instrument for overcoming the limits these kind of firms typically face in an increasingly internationally competitive and innovation-based environment. We study the effects of a well-defined type of formal network: the *network contract* that, as explained in Appendix, consists in a legal agreement between participating firms. Firms (voluntarily) signing the network contract do not receive any other kind of support (like training programs or other activities sponsored by the government), so that we can study the effect of networking per se.[4] Finally, our paper differs from the rest of the contributions in the literature also for what concerns the methods used. Specifically, we analyze the effect of networking on a firm's technical efficiency estimated through DEA methods, which provide a complementary analysis with respect to studies that make use firms' profitability or other performance measures.

2.2 Female leadership and performance

Due to the recent increase in female participation in business leadership positions, a growing—but separate—body of the literature investigates if and how women business leaders affect firm outcomes. Studies differ in terms of type of firms investigated (listed versus non-listed firms, large corporations

[3] Watson (2011) considers firms linked to *weak formal* networks (industry associations, business consultants, or banks) as well as to *strong informal* networks (other firms in the industry, family, and friends).

[4] However, networking is a multifaceted phenomenon, and we cannot exclude the existence of other forms of cooperation among firms. See Cisi et al. (2016) for more details on this issue.

versus SMEs, manufacturing firms versus firms active in service industries), country representativeness (single country versus cross-country studies), distinctive role of women (CEOs, top managers, executive versus non-executive board members), and performance measures used as left hand side variables (Tobin's q, ROA, ROE, labor productivity, TFP). Overall, results are mixed and rather far from being conclusive. As stated by Gagliarducci and Paserman (2015, p. 351), "On the whole, the literature on firm performance finds little evidence of positive effect of female leadership on firm outcomes, with some studies in fact finding evidence of negative effects. Even when the effects are positive, the results are sometimes qualified, and not always robust to econometric methods that account more credibly for potential endogeneity of the female leadership variable". In the same line, Pletzer et al. (2015), after having performed a meta-analysis of studies on the link between female representation on corporate board and firm financial performance, conclude that "The mere representation of females on corporate boards is not related to firm financial performance if other factors are not considered" (p. 1).

A seminal paper on female representation in boardrooms is Adams and Ferreira (2009), who found for the USA that, after accounting for endogeneity issues, the average effect of gender diversity on firm performance (measured with ROA and Tobin's q) is negative. This result suggests that mandated gender quotas for directors, which have recently been introduced in several European countries, can reduce firm value. A group of papers (Ahern and Dittmar 2012; Matsa and Miller 2013) exploited the introduction of gender quotas in Norway as a natural experiment, and found, indeed, negative performance effects. In a similar vein, both Gregory-Smith et al. (2013) and Ferrari et al. (2016) found for the UK and for Italy, respectively, no support for the argument that gender diverse boards enhance corporate performance (measured with both market based and accounting based measures). Interestingly, using European data on Belgian, French, Italian, and Spanish listed firms, Comi et al. (2017) confirmed the absence of a significant effect when using ROA indices in the whole sample. However, for Italy and Spain, they found evidence of a positive effect of gender quotas when labor productivity or total factor productivity (TFP) is used as an alternative metric of performance.

Using a sample of large listed European firms, Green and Homroy (2018) found a modest positive effect of female representation on board of directors on ROA, but the impact was much stronger (three times as big) when female were also members of board committees. This suggests that it is not the mere participation to the board of directors that matters, rather the presence of women in board committees, where monitoring (through the audit committee) and crucial decisions about nominations, promotions, bonuses, and premia are taken.

Several papers move away from the analysis of the role of women in board of directors (within or outside the context of mandated gender quotas) and focus more generally on female leadership, for example by looking at the gender of the CEO or at female representation in top management. Dezso and Ross (2012), for instance, look at the S&P 1500 firms and find that female managers have a positive impact on corporate performance (measured with Tobin's q) only when a firm's strategy is focused on innovation: "in which context the improvements in group decision making associated with gender diversity and the managerial attributes of women managers themselves are likely to be especially important" (p. 1073). This result has been confirmed and generalized by Christiansen et al. (2016), who found for a sample of 2 million (listed and non-listed) companies across 34 European countries that the effect of the share of women in senior positions on ROA was more pronounced in sectors that employ a higher share of women and in high-tech and knowledge-intensive industries. As the authors speculate, such industries "demand higher creativity and critical thinking that diversity in general may bring" (p. 6).

The link between female managers and female workers employed in the firms has been investigated also by Flabbi et al. (2019). Using a sample of Italian firms with at least 50 workers observed over the period 1982–1997, they found that the interaction between female leadership (i.e., the presence of a female CEO) and the share of female workers has a positive impact on performance (measured with labor productivity or total factor productivity). Therefore, they conclude that one advantage of having female leadership is that female managers are better quipped at interpreting signals of productivity from female workers and consequently improve the allocation of female talents within the firm by counteracting pre-existing statistical discrimination from male executives.

2.3 Gender and networking

The literature on differences in women and men networking modalities mostly concentrates on the role of personal networks in stimulating entrepreneurial activities of *individuals*, rather than on *firm level* networking driven by decision makers such as top managers or board members. However, the results stemming from such studies are interesting for our purpose, especially when we come to the interpretation of the interaction term between female leadership and firm networking.

Aldrich (1989) argues that networks are a crucial component of the entrepreneurial process, as entrepreneurs are embedded in social contexts that channel and facilitate, as well as constrain and inhibit, their activities. To that respect, women are disadvantaged and excluded from important social relationships and, in order to start a business, they need to carefully and systematically plan and monitor their networking activities, and they should try to increase the diversity of their connections. Building on Aldrich's framework, Cromie and Birley (1992) collected data on the size, diversity, density, and effectiveness of the networks of 274 entrepreneurs in Northern Ireland, finding that, somewhat contrary to expectations, female and male networks had a similar density and diversity. However, women tended to rely upon a male colleague as their prime contact but to revert to female links for all subsequent contacts, while men relied more on contacts with other men. Klyver and Grant (2010) used a sample of more than 300,000 individuals in 35 countries and found that individuals who personally knew an entrepreneur were more likely to start a business. However, women were less likely to be acquainted with an entrepreneur, so that their limited entrepreneurial activity could be explained by the lack of entrepreneurial resource providers or role models in female social networks. Moving from the argument that females have limited contacts compared to men and are less involved in networking, especially if it is of the formalized type, Watson (2011) investigated the role of different formal and informal networks for both female and male controlled SMEs, finding the absence of any discernible gender effect on firm survival or growth. McAdam et al. (2018) focused on the effectiveness of a policy intervention in Northern Ireland, where the regional development agency established women-only formal networks, with the aim of helping women entrepreneurs to access to economic, social, and cultural capital. Using data from qualitative interviews, the authors are rather skeptical about the success of such an initiative, suggesting that separatist women-only solutions have limited efficacy, if any.[5]

Coming to rather different conclusions is the recent work of Kuhn and Villeval (2015). Analyzing individuals and teams at work, these authors find that women are generally more proficient in cooperation, and teams created by women work better together, obtaining higher performances. Summarizing the current state of literature Hanson and Blake (2009) in a recent survey, note that "The literature on entrepreneurial networks and gender is so poorly developed that the main take-away message is simply how little is known" (p. 146). Ultimately, the issue of whether or not female leaders contribute to a firm's performance also through their different "style of networking," over and beyond their different managerial style, is an empirical one, on which only minimal evidence is currently available in the literature. One of the aims of our paper is to contribute to filling this gap.

2.4 Female leaders in the digital era

In the final part of the paper, we explore the existence of any heterogeneity related on whether or not female business leaders are active in innovative sectors. Apart from the usual distinction between high-tech and low-tech industries, we explore the role of digitization and, more in general, of the so-called fourth industrial revolution (Industry 4.0). Sectors differ in terms of investment in ICT hardware and software, as well as in the use of robots in the manufacturing process, in the hiring of ICT specialists and in the use of online sales. The digital transformation is part of a process labeled "fourth industrial revolution." The latest technological developments go much further than the automation of repetitive physical work, and the combined use of digitization, highly effective connectivity, and technologies such as cloud computing and artificial intelligence are leading to the large-scale automation of entire

[5] There are also some papers that investigated networking by using datasets of students and by conducting laboratory experiments. Lindenlaub and Prummer (2014) analyzed the networks formed by 90,000 US students finding that men's networks allowed members to have better access to information, while women's networks were characterized by high peer pressure. Since information is important in contexts of high uncertainty and peer pressure is more valuable when there is limited uncertainty, they argued that men outperform women when there is high earnings uncertainty. Friebel et al. (2017) ran a laboratory experiment using a sample of German students and found that women's social networks were more stable, path-dependent, and exhibited strong links, while men formed less selective and more opportunistic networks.

group of tasks, including repetitive intellectual tasks previously performed by human beings.[6] While this process is creating new business opportunities, it involves also the displacement of workers that are performing routine and replaceable tasks. Technical skills will be far less important in the future, with personal skills becoming more critical. For example, employees will need to shift their focus to the things machines cannot do—the ability to read people's emotions and react accordingly, or think creatively. The so-called *soft skills* that are required go from cognitive flexibility to critical thinking, from the ability to coordinate with others to complex problem solving skills (World Economic Forum 2018). A priori, it is unclear how the productivity impact of networks and female leaders should be expected to differ in traditional industries as opposed to sectors that are rapidly going digital. From the one hand, a persistent gender digital gap, documented to exist even for younger cohorts and already visible at early stages in labor market careers, partly because of different human capital investments in STEM subjects, suggests that women may be less favorably placed than men to take full advantage of the new digital environment. On the other hand, one may argue that the rapid advances in information and communication technologies, and the emphasis placed on soft skills in the new competitive setting, may allow women to fuller exploit their comparative advantage in networking activities, when compared to men. The role of innovation, ICT, and digitization is particularly important for a country like Italy. As has been recently demonstrated by Pellegrino and Zingales (2018), the productivity slowdown of Italy heavily depends on the failure of firms to take full advantage of the ICT revolution, and this failure is, in turn, due to familism, cronyism, and the lack of meritocracy in the selection and rewarding of talented managers.

3 Methodology

3.1 Modeling the technical efficiency of manufacturing firms

In the present paper, we adopt as measure of firm performance based on a standard semi parametric version of technical efficiency, estimated through Data Envelopment Analysis and its bias corrected version. The main advantage of using DEA is that it does not require to specify a form for the technology representing the production process, so that no assumptions are made for the shape of the production frontier. Moreover, DEA allows computing a simple inefficiency measure also for a technology involving multiple outputs and multiple inputs: The frontier is directly derived from the data, and all firms in the sample are evaluated through input or output distance.

We consider a vector of inputs $x = (x_1, \ldots, x_N) \in R_+^N$ which are combined in order to obtain a vector of outputs $y = (y_1, \ldots, y_M) \in R_+^M$. The output set $P(x) = \{y : x \text{ can produce } y\}, x \in R_+^N$ consists of combinations of output compatible with input bundles; if the set is closed and convex, a standard and DEA efficiency score can be defined as:

$$\lambda_{DEA}(x_0, y_0) = \sup\{\lambda \mid \lambda y_0 \in P(x_0)\} \tag{1}$$

This theoretical indicator of efficiency can be operationalized using the linear programming framework, by solving K linear programs, one for each firm in the sample, repeating the procedure for each specific production process involved in the analysis. Under the assumption of variable return to scale, more respondent to the real production processes of manufacturing industries, the model appears as follows:

$$\begin{aligned} &\widehat{\lambda}_{DEA}(x_0, y_0) = \max \lambda \\ s.t. \quad & x_0 \geq \textstyle\sum_{k=1}^{K} z_k X_k; \\ & \lambda y_0 \leq \textstyle\sum_{k=1}^{K} z_k Y_k; \\ & z_k \geq 0; \\ & \textstyle\sum_{k=1}^{K} z_k = 1, \end{aligned} \tag{2}$$

where k indicates firms (i.e., decision making units or DMUs), and X and Y are matrices of inputs and outputs. More recent extensions of the classical DEA model try to partially mitigate one of the main disadvantages of this deterministic approach, i.e., the absence of a stochastic error component. Simar and Wilson (1998) show that $\hat{\lambda}_{DEA}$ scores are, by construction, biased and overestimate the true technical efficiency level. Following their contributions, to which we refer for any technical details, the BIAS can be defined as:

$$\text{BIAS}\left(\widehat{\lambda}_{DEA}(x_0, y_0)\right) = E\left(\widehat{\lambda}_{DEA}(x_0, y_0)\right) - \lambda_{DEA}(x_0, y_0) \tag{3}$$

[6] Examples are smart factories that operate autonomously, autonomous vehicles, smart electricity grids, 3D printers, the deployment of objects equipped with computing capabilities and connected to communication networks in healthcare and agriculture (the so called *internet of things*), and so on.

where $\lambda_{DEA}(x_0, y_0)$ represents the true technical efficiency score that remains unknown. Using a homogeneous bootstrap, Simar and Wilson (1998) introduce a method for estimating the BIAS, based on the assumption that the true production set boundaries lie to the left and above the piecewise linear frontier. Under such an assumption, an estimate of DEA scores corrected for the potential bias can be derived as follows:

$$\widehat{\widehat{\lambda}}_{DEA}(x_0, y_0) = \widehat{\lambda}_{DEA}(x_0, y_0) - \widehat{BIAS}_{Boot}\left(\widehat{\lambda}_{DEA}(x_0, y_0)\right) \quad (4)$$

These bias-corrected efficiency scores in their output-oriented format are bounded below by 1, a value never reached for the application of the correction procedure. Therefore, values near to 1 represent the most efficient firms in the sample, in terms of their ability in combining inputs to obtain output.

3.2 Truncated regression and separability issues

As argued by Simar and Wilson (2007) in their seminal paper, the use of standard regression models is problematic in the analysis of efficiency scores. Given the complex nature of data generating process and the complicated correlation structure for the residuals, standard econometric techniques (i.e., OLS or Censored Tobit models) fail to estimate unbiased coefficients of interest. For mitigating the problem, Simar and Wilson (2007, 2011) propose an identification strategy based on truncated regression estimated via maximum likelihood:

$$\widehat{\widehat{\lambda}}_{DEA}(x_0, y_0) = w\mathrm{k}\,\gamma + \varepsilon\mathrm{k} \geq 1, k = 1, \ldots K \quad (5)$$

where $\varepsilon_{\mathrm{i}} \sim N(1,\ \sigma_{\varepsilon}^2)$ before truncation and w_{k} represents a generic set of firm-level variables which potentially affect technical efficiency performance. The unknown real efficiency scores $\hat{\hat{\hat{\lambda}}}_{DEA}(x_0, y_0)$, based on an unknown technological frontier, are estimated according to the DEA framework with bootstrap by $\hat{\hat{\hat{\lambda}}}_{DEA}(x_0, y_0)$, through a first stage analysis following the methodological insight reported in the previous section. The model is then estimated via maximum likelihood, by applying a truncated regression procedure. To obtain a more reliable confidence interval, a bootstrap procedure is also performed in the ML estimation of the truncated model. The sequence of actions as well as additional information on all bootstrap phases can be found in Simar and Wilson (2007) that remains the baseline reference for all technical questions. There is a number of recent applications of such a method, even if many of them do not incorporate some important and recent theoretical developments. For instance, using balance sheet data from Chinese banks, Du et al. (2018) analyze efficiency scores in a panel-structured framework, with an approach similar, also in terms of control variables introduced, to that used by Devicienti et al. (2017) on a sample of Italian manufacturing firms. Biener et al. (2016) include many firm characteristics (i.e., leverage and international diversification degree, among the others) as regressors for investigating their effect on efficiency in the Swiss insurance sector. Other applications are Chowdhur and Zelenyuk (2016), who analyze the efficiency of hospitals services or Bruno and Manello (2015), who focus on the telecommunications sector. Nevertheless, when interpreting regression results, Simar and Wilson (2011), Bâdin et al. (2012), and, more recently, Daraio et al. (2018) show that the application of the truncated regression is valid (i.e., estimated coefficients are meaningful) only if separability conditions between the input-output space and explanatory variables hold. If the hypothesis on separability is rejected, the coefficients from the regression cannot be correctly interpreted, and the precision of estimates is weaker. As suggested by Devicienti et al. (2017), separability implies that external factors influence the production process only through the conditional density function (i.e., the probability of lying on the frontier, for any given level of external factors), without influencing its support. In their recent contribution, Daraio et al. (2018) propose a specific test on separability conditions that should be run before applying truncated regressions on efficiency scores. In our study, the above-mentioned test allows to verify separability for the two main aspects of interest: network membership and the presence of female leaders. In general terms, the test consists in comparing the efficiency scores computed in a standard setting with the efficiency scores computed in a conditional setting, where conditional variables are those entering as regressors in the truncated regression phase. If separability is valid, estimates from

Table 1 Networking activities and female leadership positions

		Networking activities (end of 2015)		
		No	Yes	Total
Female top leaders	No	65,939	1593	67,532
	Yes	16,578	352	16,930
	Total	82,517	1945	84,462

the two settings should not differ so much, and a normally distributed t test can be used as in standard hypothesis testing.

4 Data

4.1 General overview and main sources

Our main source of information is the AIDA dataset provided by Bureau Van Dijk, which contains detailed financial information of Italian firms. The data refers to the whole population of firms that are compelled to register their profit and loss accounts and balance sheets according to Italian law, i.e., limited companies and corporations. Starting with this population, we decided to focus on the manufacturing sector, because of the stronger correspondence between the production process and the assumption of the DEA model. Using the tax code as a firm identifier, we matched the AIDA financial database with information on all the firms involved into networking activities (i.e., firms that signed a *network contract*), as collected by the INFOCAMERE database. The available information refers to the network name, number, and identity of partners, main objects of the agreement, month and year of the network creation.

4.2 Descriptive statistics and data issues

Given the large dimension of the database, we devote strong attention to the presence of unreliable or incomplete balance sheet data, mainly for the sensitivity of DEA models to the presence of outliers, and we implement a careful process of data cleaning. All efficiency computations are based on the last economic/financial information, referred to the 2016 balance sheet. First, firms that became inactive during 2016, as well as firms involved in liquidation processes, are excluded from the sample. Second, we eliminate unreliable or out-of-scale balance sheet data, excluding all firms with evident data alterations or errors. Third, after computing a rough indicator of labor productivity (i.e., revenues per unit of labor cost), we exclude potential outliers by eliminating firms showing too large (over the 99th percentile) or too small (under the 1st percentile) values. This procedure for the identification of outliers has been performed at the two-digit NACE disaggregation. Finally, we include in the sample only firms for which we are able to retrieve information on leadership roles through the analysis of the AIDA section devoted to the collection of names and positions of top managers and of members of the board of directors (if present). The final sample for which we are able to consistently estimate DEA efficiency scores is composed by 84,462 manufacturing firms which are classified in 16 homogeneous technologies, for which DEA models are computed separately. We use three inputs—intermediate goods and services (M), labor (L), and fixed capital (K)—and one output (Y)—the total value of production (revenues net of change in inventories). All variables we use in the DEA computations are referred to the year 2016; fixed capital has been proxied by the total asset net of depreciation and amortizations, and labor (L) has been proxied by total labor costs,[7] while intermediate goods and services (M) have been proxied by the sum of raw material costs (net of inventories changes), services, and the cost of leased assets. We structured our database as a cross-sectional database with retrospective information, where financial variables refer to the period 2014–2016.

Table 1 shows the descriptive statistics on the adoption of network agreements and on female representation in leadership roles for the reference sample. The number of manufacturing firms involved in network agreements at the end of 2015 is 1945 (2.3% of the total sample). Around 20% of firms has at least one woman at the top of the corporate ladder, where leading positions include the CEO, the president of the board of directors (when there is a board), or, in the case of very small firms, executive administrators or directors.

Table 2 reports the average efficiency scores obtained in the DEA first-stage. We computed these scores according to the bias-correction procedure described in

[7] We use labor cost to overcome problems due to the identification of the number of full-time equivalent workers and to the difference in the quality of the workforce.

Table 2 Technical (in) efficiency scores

NACE codes	Mean	Standard deviation	99th percentile	Number of firms
Food and beverage	2.896	1.158	6.654	7433
Textiles, clothing, and leather	2.243	0.703	4.687	9337
Wood	1.675	0.479	3.261	2608
Paper products	1.566	0.310	2.434	1457
Printing	1.984	0.378	2.923	2644
Chemicals and pharmaceutics	2.359	0.797	4.792	2847
Plastic and rubber	2.706	1.123	6.376	4045
Minerals products	3.390	1.437	7.421	3971
Metal products	2.474	0.742	4.522	19,043
Electronic equipment	2.249	0.722	4.559	5854
Machinery	2.526	0.717	4.592	9868
Vehicles	6.658	3.838	14.786	1613
Furniture	1.762	0.548	3.447	3175
Other manufacturing industries	2.599	1.070	5.741	2690
Maintenance services	2.197	0.850	5.399	3650
Electricity production	3.405	1.694	9.642	4227
Total	2.563	1.261	7.781	84,462

Sect. 3, and separately for each industry identified through a slight recombination of two-digit NACE codes.[8] All sectors considered count thousands of firms, so that we could run the DEA models separately for each of the sector reported without incurring in any kind of dimensionality problems. The entire sample shows an average inefficiency score of 2.5, substantially in line with previous studies employing balance sheet data (see, for instance, Manello et al. 2016).

4.3 Empirical strategy and main variables used

Our empirical approach is to estimate different variants of the model in (6):

$$\widehat{\widehat{\lambda}}_{DEA\,kt} = \beta N_{kt-1} + \mu F_{kt-1} + \delta Z_{kt-1} + S_k + R_k + \varepsilon_{kt} \geq 1, \quad k = 1, \ldots K \tag{6}$$

where $\widehat{\widehat{\lambda}}_{DEA\,kt}$ represents the measure of technical inefficiency estimated using the 2016 financial data, while all firms' characteristics and controls on the right-hand side of (6) refer to the previous year (2015), so as to mitigate simultaneity (endogeneity) problems. Indeed, given that also networking status and female representation might be potentially endogenous, as suggested by Green and Homroy (2018), we decide to lag by one period *all* the independent variables included in the regressions. This procedure may clearly be insufficient to dispel residual concerns related to endogeneity and convincingly establish causality. To further prove the robustness of our results to the potential endogeneity of the main variables of interest, in the final section of the paper, we rely on the application of a control function approach within the DEA second-stage framework.[9]

The coefficients β and μ capture the relationship between technical inefficiency and, respectively, networking (indicated by N_{kt-1}) and female representation (denoted by F_{kt-1}). The vector Z_{kt-1} accounts for lagged firms characteristics or controls, such as firm's size and age, while S_k and R_k represent sectoral and regional fixed effects.

Concerning networks, using lagged values is equivalent to focus on all the network agreements created during the year 2015 and before. This idea, other than

[8] We gather, respectively, food and beverages, chemical products and pharmaceuticals, and textile and leather products.

[9] Exploiting the panel-dimension to control for firm fixed effects is not easily accommodated within our DEA framework: The assumption of time-invariant firm fixed effects is problematic in the presence of year-specific technical frontiers based on different input bundles or techniques which could be simply not available during different years.

mitigating simultaneity issues, also reflects the nature of these agreements: After the network contract is signed, it is reasonable to assume that it takes some time before it becomes operative. Therefore, we consider as "networking firms" only those that stipulate the contract in 2015 or before, while firms entering networks in 2016 are in a sort of "transition period": The network has been set-up, but its effects cannot influence the balance sheets. According to this, we create a dummy named *Networking*, identifying firms participating to network agreements at the end of year 2015.

Data on female representation is drawn from AIDA, too. In particular, for each firm, we compute the total number of persons identified as top leaders and we retrieve the information on their gender. We then create a dummy variable, which we name *Female_top_dummy*, indicating that at least one woman appears among top leadership roles, according to the approach followed by Campbell and Minguez-Vera (2008). We also compute the share of females among top leaders, following Devicienti et al. (2018), and name this variable *Female_top_share*.

Additional control variables, used to partially reduce the observed heterogeneity of technical efficiency scores among different manufacturing firms, are drawn from the managerial literature as well as from empirical studies on the determinants of performance (Nickell et al. 1997; Zelenyuk and Zheka 2006). We include a measure of a firm's *Size*, computed as the natural logarithm of the number of employees in 2015; the firm's *Age*, obtained as the difference between 2015 and the year of the firm's foundation; and a measure of *Vertical disintegration*, computed as the ratio between external cost components (i.e., raw materials, services and rents) over total production costs. Moreover, even if the different level of investment or fixed capital is implicitly incorporated by using physical assets as the capital input into the DEA models, we also include as an additional control a proxy for the degree of *Mechanization*, computed as fixed assets over labor costs in 2015.

To increase our confidence in the suitability of the truncated regression model in the current application, we conducted a simplified version of the test introduced by Daraio et al. (2018), to which we refer for all technical details. In particular, we perform the test with respect to the two key aspects of the analysis, i.e., networking and the female participation dummies. The test is based on the idea of comparing unconditional and conditional efficiency scores, where the conditioning variables are the main variables of interest. We apply the test in three ways: We first consider each single dummy one-by-one, and then we consider the case resulting from combining the two variables, i.e., the subgroup of firms with female leadership that participate to networks. The null hypothesis of equally distributed efficiency scores across the conditional and unconditional settings can be accepted, at conventional statistical levels, in all three cases.[10] Therefore, we are relatively confident that the separability conditions are satisfied in our empirical application, at least with reference to our main aspects of interest. Comforted by this result, we next proceed with the second-stage regressions in (6), which are interpreted in the usual way.

5 Results

5.1 Technical efficiency and networking

Before interpreting our results, we observe that the analyzed efficiency scores, distributed between 1 and $+\infty$ according to the Simar and Wilson (2007) specification, indicate for each firm its specific level of inefficiency. We apply the double bootstrap procedure (i.e., 1000 replications in the first stage and 1000 replications for all truncated regressions) to all estimates. The maximum likelihood method then guarantees the reliability of the confidence intervals proposed. All coefficients reported indicate the impact of each variable on the level of inefficiency. Notice that a negative sign indicates that effect on efficiency is positive.

We begin by showing the impact of networking on technical efficiency scores, disregarding the effect that having females at the top of the corporate ladder might have on performance. Column (1) of Table 3 shows that firms involved in formal network agreements display higher technical efficiency scores, with a positive differential of around 0.08. After entering a network agreement, firms seem to increase their capacity of obtaining output per unit of inputs employed, which we interpret as the result of stronger cooperation and resources sharing with other network members. The observed effect is relatively small in magnitude, but it remains stable and always statistically significant across all specifications, as we will see.

[10] Details on the numerical results of the test are available upon request.

Table 3 Effect of networking on technical efficiency scores and on labor productivity

Variables	(1) Dependent variable: DEA inefficiency scores bias corrected	(2)
Networking	− 0.0826**	− 0.0757*
	(− 0.163–0.00191)	(− 0.156–0.00428)
Size	− 0.593***	− 0.589***
	(− 0.613–0.574)	(− 0.609–0.569)
Age	− 0.000607	− 0.000396
	(− 0.00150–0.000284)	(− 0.00131–0.000518)
Vertical disintegration	− 1.952***	− 2.009***
	(− 2.047–1.856)	(− 2.110–1.908)
Mechanization	− 0.000146**	− 0.000117
	(− 0.000274–1.92e-05)	(− 0.000860–0.000627)
Macroarea fixed effects	Yes	No
Regional fixed effects	No	Yes
Industrial fixed effects	Yes	Yes
Constant	5.820***	5.737***
	(5.719–5.922)	(5.623–5.850)
Sigma	1.303***	1.273***
	(1.269–1.338)	(1.237–1.309)
Observations	84,462	84,462
Chi-square	5,223	4,794
Log-likelihood	− 111,048	− 99,763

Robust confidence intervals in parentheses

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

For what concerns the evidence on other controls, from the first two columns of Table 3, the variable *Size* shows an expected positive impact on efficiency, in line with other works (Devicienti et al. 2017; Latruffe et al. 2008). Contrary to expectations, a firm's past experience, as proxied by the firm's age, does not seem to exert a significant influence on efficiency. Finally, the level of outsourcing, measured by external costs over total costs, has a strong positive impact on technical efficiency, confirming previous findings reported by Pieri and Zaninotto (2013) and Manello et al. (2016). Our vertical disintegration control variable contributes to reduce heterogeneity deriving from the strong differences in outsourcing strategies and in vertical boundaries that characterize manufacturing firms, even when they operate in the same sector.

5.2 Female leadership and networking activities

We next augment our truncated regression models including information on the presence of female at the top of the corporate ladder. The results, reported in Table 4, lend support to the view that female representation might have a detrimental impact on a firm's efficiency. As anticipated, we use two different ways to account for female participation: We include a dummy variable indicating if at least one top leader is a woman (Table 4, models 1, 2, and 4) and a continuous variable indicating the share of females in leadership roles (Table 4, model 3).[11] The presence of women (*Female_top_dummy*) always displays a positive and statistically significant coefficient, with a positive differential in terms of technical inefficiency scores of around 0.035, which remains quite stable across all specifications. When female representation is investigated in combination with networks (Table 4, model 2–4), the previous results are confirmed. The negative impact of female participation on efficiency is confirmed both in the case of the dummy (Table 4, model 2) and in the

[11] We include also the number of top leaders (Top Leader N), which is never found to be significant.

Table 4 The impact of female representation in leading positions and of networking on efficiency

Variables	Dependent variable: DEA inefficiency scores bias corrected using homogeneous bootstrap			
	(1)	(2)	(3)	(4)
Female_top_dummy	0.0351**	0.0350**	–	0.0427***
	(0.00579–0.0643)	(0.00571–0.0642)		(0.0126–0.0727)
Female_top_share	–	–	0.0313*	–
			(− 0.00155–0.0641)	
Networking	–	− 0.0754*	− 0.0883**	− 0.0296
		(− 0.155–0.00463)	(− 0.167–0.00946)	(− 0.120–0.0612)
Female*Networking	–	–	–	− 0.234***
				(− 0.386–0.0817)
Top leader N	–	–	− 0.0123	− 0.0155
			(− 0.0391–0.0145)	(− 0.0424–0.0113)
Size	− 0.589***	− 0.588***	− 0.586***	− 0.588***
	(− 0.609–0.569)	(− 0.608–0.568)	(− 0.606–0.566)	(− 0.608–0.568)
Age	− 0.00375	− 0.00371	− 0.00321	− 0.00340
	(− 0.00129–0.00539)	(− 0.00128–0.00543)	(− 0.00124–0.00594)	(− 0.00125–0.00574)
Vertical disintegration	− 2.004***	− 2.003***	− 2.000***	− 2.001***
	(− 2.105–1.902)	(− 2.105–1.902)	(− 2.101–1.898)	(− 2.102–1.900)
Mechanization	− 0.00108	− 0.00107	− 0.00114	− 0.00103
	(− 0.00852–0.000636)	(− 0.00850–0.00637)	(− 0.00864–0.00635)	(− 0.00846–0.00640)
Regional fixed effects	Yes	Yes	Yes	Yes
Industrial fixed effects	Yes	Yes	Yes	Yes
Constant	5.727***	5.726***	5.741***	5.740***
	(5.613–5.842)	(5.612–5.840)	(5.623–5.859)	(5.623–5.858)
Sigma	1.273***	1.273***	1.271***	1.273***
	(1.237–1.309)	(1.237–1.309)	(1.235–1.307)	(1.237–1.309)
Observations	84,462	84,462	84,462	84,462
Chi-square	4,799	4,798	4,793	4,801
Log-likelihood	− 99,761	− 99,760	− 99,190	− 99,756

Robust confidence intervals in parentheses

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

case of the female share among top leaders (Table 4, model 3). Notice, also, that the positive effect of networking is confirmed, with point estimates similar to the ones reported in Table 3.

The last column of Table 4 includes the interaction between *Female_top_dummy* and *Networking* (*Female*Networking*). While the pure ("direct") effect of female leadership roles on efficiency remains negative, the interaction term has a negative and statistically significant coefficient, implying a positive effect. Accordingly, engaging in networking activities is particularly beneficial for firms characterized by the presence of female leaders, as opposed to firms led only by men. The estimated coefficient of the interaction term is large in magnitude (− 0.234). Considering the average efficiency scores recorded in the sample, this estimate implies a positive efficiency differential of around 10%, on average, in favor of networking firms characterized by the presence of female leaders. This result suggests that female leaders play a crucial role in the organization and functioning of the network contract. Importantly, the interacted term more than compensates the general negative effect that, per se, the presence of a female top leader seems to have on a firm's performance. This result is new in the literature but is in line with recent experimental findings reported by Kuhn and Villeval

Table 5 The impact of female leadership and networking: female-friendly networks and female intensive sectors

Variables	(1) Full sample	(2) Low female employment	(3) High female employment
Female_top_dummy	0.0401***	0.0515**	0.0292
	(0.0102–0.0700)	(0.0112–0.0919)	(− 0.00787–0.0663)
Networking	− 0.0314	− 0.00687	− 0.0796
	(− 0.148–0.0854)	(− 0.127–0.113)	(− 0.183–0.0240)
Mixed female networks	− 0.0329	–	–
	(− 0.206–0.140)		
Female friendly networks	− 0.211*	–	–
	(− 0.438–0.0165)		
Female*Networking	–	− 0.260**	− 0.154*
		(− 0.477–0.0428)	(− 0.314–0.00702)
Top leader N	− 0.0157	− 0.0124	− 0.0187
	(− 0.0425–0.0112)	(− 0.0484–0.0237)	(− 0.0484–0.0110)
Size	− 0.588***	− 0.645***	− 0.423***
	(− 0.608–0.568)	(− 0.670–0.619)	(− 0.451–0.395)
Age	− 0.00346	− 0.00231	− 0.00606
	(− 0.0126–0.00568)	(− 0.00145–0.00994)	(− 0.00179–0.00582)
Vertical disintegration	− 2.002***	− 2.239***	− 1.356***
	(− 2.103–1.900)	(− 2.371–2.107)	(− 1.487–1.225)
Mechanization	− 0.00105	− 0.00489	0.00393**
	(− 0.00848–0.00638)	(− 0.0013–0.00036)	(0.00081–0.0071)
Regional dummies	Yes	Yes	Yes
Industrial dummies	Yes	Yes	Yes
Constant	5.742***	5.935***	4.311***
	(5.624–5.859)	(5.793–6.077)	(4.166–4.457)
Sigma	1.273***	1.378***	0.946***
	(1.237–1.309)	(1.333–1.423)	(0.897–0.996)
Observations	84,462	62,922	21,540
Chi-square	4,799	3,690	1,516
Log-likelihood	− 99,758	− 75,802	− 23,175

Robust confidence intervals in parentheses

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

(2015). In terms of technical efficiency, our results substantially confirm their main findings: Networks of firms characterized by an active role of women perform better (10% better on average) than more traditional, male-dominated networks.

5.3 Female friendly networks and firm performance

In this section, we further explore the interplay between female leadership roles and networking, by exploiting detailed information on the firms participating to the various network agreements. We are able to identify three categories of networks. First, we isolate networks composed by firms where female do not participate to the firm's pivotal decisions, i.e., where top leaders are only male. There are 949 firms in such "male-only" networks. Second, we identify networks in an intermediate situation, where there is a certain degree of female participation in the decision making, i.e., where less than half of network members have at least one woman among top leaders. Within this category, we found 708 firms, who are identified through the dummy *Mixed* *female networks*. Third, in female-friendly networks, more than half of the participating firms exhibit at least one female decision maker. There are 288 firms in this category, which are identified with the dummy *Female-friendly networks*.

The estimates reported in Table 5, column (1), confirm our previous findings that female participation per se has a negative effect on efficiency, while the positive effect of networking on efficiency disappears, as in our baseline model 4 of Table 4. The two dummies *Mixed female networks* and *Female-friendly networks* are negatively signed, but only the latter is statistically significant. This suggests that the positive effect of networking on performance is stronger whenever the participation of women in leadership roles is pervasive within the network, i.e., where the majority of members has at least one woman among their top decision makers.

In order to investigate how female participation in top roles interacts with the more general gender composition of a firm's workforce, we run separate regressions for the subsample of firms operating in "male intensive" sectors, i.e., where the share of female employees is below the average, and for the group of firms active in "female intensive" sectors, i.e., where the share of female employees is above the average.[12] As shown by column 2 of Table 5, in the first cluster, the negative effect on efficiency of female representation is confirmed, and the estimated coefficient is larger than for the full sample. This seems in line with the evidence in Lucifora and Vigani (2016), who document, for the Italian context, the possibility of organizational, coordination, and communication frictions in firms where women bosses are surrounded by male subordinates. Moreover, in male intensive contexts, networks among female-lead firms have significantly higher technical performances, as shown by the estimated coefficients of the dummy *Female*Network*. The estimated coefficient is larger, in absolute value, than the value for the full sample reported in Table 4 (− 0.260 against − 0.234), confirming that networking can be an effective means for female leaders to increase their impact on a firm's performance, especially in male-intensive environments where a female leader's job might be more challenging.

In female intensive sectors, the negative effect from female participation in the top positions halves and becomes statistically insignificant, while the effect of network agreements among female-leading firms is lower (− 0.154) than for the full sample. This evidence suggests that female leaders per se are not necessarily detrimental to performance; the detrimental effects seem to emerge mostly in combination with some industry specificities, such as those related to a higher male intensity in the workforce. In fact, our results support the idea that, with reference to the full sample of manufacturing firms, mainly operating in male oriented sectors, the "rare" female top leaders participate to decisions into relatively "hostile" environments. However, when we consider more "familiar" (to women) environments, i.e., characterized by a strong presence of female workers, the negative effects of female leaders on firm performance disappear, in line with the results of Flabbi et al. (2019).

The above results are compatible with two "stories" that can be labeled the "pipeline" hypothesis and the "backlash hypothesis".[13] Assume that a company employs a majority of men and a minority of women, and that one or few women get promoted. According to the "pipeline" hypothesis, there is not a sufficient pool of females and when a female is promoted it is more likely that she is not of comparable quality to a male manager. Soe and Jakura (2008) and Fernandez-Mateo and Fernandez (2016) argue that the underrepresentation of women in top layers of management is often attributed to a shortage of women "in the pipeline" and that in the passage from one stage to the next the flow (supply) of women diminishes. This happens for two main reasons: failing to progress and "leakage" from the pipeline (i.e., women choose other options, for example to manage home and children). According to the "backlash" hypothesis, companies that are dominated by men feel a disruption when a talented woman is appointed as a top manager. If there is a backlash against the new manager, resources are wasted unfruitfully, since, on the one hand, she is forced to invest in defending herself, while, on the other hand, males spend time in getting in her way. Regrettably, with our data, we have no way to investigate the relative importance of the two hypotheses in generating the differential impact of female leadership in

[12] To compute the average female share on total employees for each two-digit NACE manufacturing sector, we resort a dataset based on an Italian firm-level survey (the Employer and Employee Survey -RIL) conducted by the Institute for the Development of Workers' Vocational Training (ISFOL).

[13] We are indebted to an anonymous referee for suggesting us such an interpretation.

Table 6 Breakdown by industry innovation intensity and digitalization level

Variables	(1) High-tech	(2) Low-tech	(3) Digital	(4) Not digital
Female_top_dummy	0.0233	0.0531***	0.0287	0.0719***
	(− 0.0269–0.0734)	(0.0171–0.0891)	(− 0.00884–0.0663)	(0.0226–0.121)
Networking	− 0.0376	− 0.0514	− 0.0177	− 0.0973
	(− 0.190–0.115)	(− 0.143–0.0403)	(− 0.132–0.0965)	(− 0.230–0.0354)
Female*Networking	− 0.286**	− 0.198**	− 0.243**	− 0.212*
	(− 0.561–0.0119)	(− 0.366–0.0310)	(− 0.431–0.0541)	(− 0.463–0.0390)
Top leader N	− 0.00492	− 0.0286**	0.00284	− 0.0470**
	(− 0.0513–0.0415)	(− 0.0557–0.00142)	(− 0.0325–0.0382)	(− 0.0836–0.0105)
Size	− 0.486***	− 0.665***	− 0.502***	− 0.719***
	(− 0.515–0.458)	(− 0.693–0.638)	(− 0.526–0.478)	(− 0.754–0.683)
Age	− 0.00162*	0.000636	− 0.00168***	0.00186**
	(− 0.00325–3.83e-06)	(− 0.000393–0.00167)	(− 0.00286–0.000512)	(0.000425–0.00329)
Vertical disintegration	− 2.068***	− 1.902***	− 1.798***	− 2.302***
	(− 2.232–1.903)	(− 2.027–1.777)	(− 1.924–1.672)	(− 2.473–2.132)
Mechanization	− 7.66e-05	− 0.000426	0.000761	− 0.000891
	(− 0.00118–0.00103)	(− 0.00143–0.000575)	(− 0.00130–0.00282)	(− 0.00220–0.000420)
Regional fixed effects	Yes	Yes	Yes	Yes
Industrial fixed effects	Yes	Yes	Yes	Yes
Constant	4.484***	5.884***	9.178***	6.234***
	(4.321–4.647)	(5.739–6.029)	(8.923–9.433)	(6.046–6.422)
Sigma	1.397***	1.144***	1.277***	1.248***
	(1.335–1.458)	(1.104–1.184)	(1.228–1.325)	(1.197–1.300)
Observations	40,414	44,048	51,502	32,960
Chi-square	2,168	3,007	2,915	2,055
Log-likelihood	− 51,464	− 47,626	− 64,044	− 35,441

Robust confidence intervals in parentheses

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

predominantly-male versus predominantly-female sectors.

5.4 High-tech and digital industries

Dezso and Ross (2012) and Christiansen et al. (2016) show that the effects of female participation on firm performance are stronger when innovation is a key competitive factor, arguing that females' "different visions" are particularly valuable in these environments. To provide a contribution to this literature, in this section, we investigate the differential impact that female managers have in environments characterized by different degrees of innovation and, in particular, with different levels of digitalization. To do so, we simply divide our sample according to different intensities of our aspects of interest, and we run separate truncated regressions on each subsamples. Table 6 reports four columns of results, two relative to high-tech and low-tech sectors (using the classification proposed by Christiansen et al. 2016) and two relative to digital and non-digital industries (using the classification recently proposed by Calvino et al. 2018).[14] Table 6, models 1, shows that, while in the subsample of firms operating in traditional sectors, the results substantially confirm signs and magnitudes of the coefficients estimated in our baseline model (Table 4, column 4), and for high-tech firms, the

[14] Note that high-tech sectors and digital intensive industries only partially overlap. For example, wood, paper, printing, and furniture are traditional low-tech sectors characterized by a medium-high digital intensity. Vice versa, chemicals and pharmaceuticals are R&D intensive sectors that exhibit a medium-low degree of digital intensity.

Table 7 Propensity score in the Simar-Wilson truncated regression

Variables	*p*-score on networking		*p*-score on female leadership	
	(1)	(2)	(3)	(4)
Female_top_dummy	0.0394***	0.0429***	0.0321**	0.0359**
	(0.00997–0.0689)	(0.0131–0.0728)	(0.00280–0.0615)	(0.00623–0.0656)
Networking	− 0.061*	− 0.0174	− 0.0539*	− 0.00855
	(− 0.139–0.00263)	(− 0.106–0.0710)	(− 0.132–0.00193)	(− 0.0978–0.0807)
Female*Networking	–	− 0.213***	–	− 0.214***
		(− 0.362–0.0637)		(− 0.363–0.0650)
Propensity score	− 29.47	− 2.751	22.23***	26.21***
	(− 66.19–7.244)	(− 51.72–46.22)	(13.41–31.05)	(16.36–36.05)
Propensity score squared	228.0	42.09	− 20.85***	− 24.00***
	(− 324.1–780.0)	(− 595.5–679.7)	(− 34.79–6.909)	(− 38.11–9.894)
Propensity score cubed	− 399.3	32.82	–	–
	(− 3569–2770)	(− 3216–3282)		
Controls as in Table 4	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes
Industrial dummies	Yes	Yes	Yes	Yes
Constant	6.173***	5.752***	2.688***	2.123***
	(5.632–6.715)	(5.043–6.461)	(1.567–3.809)	(0.848–3.398)
Sigma	1.236***	1.236***	1.233***	1.232***
	(1.200–1.272)	(1.200–1.273)	(1.197–1.269)	(1.196–1.268)
Observations	80,255	80,255	80,345	80,345
Chi-square	4,782	4,788	4,671	4,680
Log-likelihood	− 93,611	− 93,623	− 93,577	− 93,536

Robust confidence intervals in parentheses. Even if not reported, we include the same controls from Table 4 but lagged 1 year more and referred to 2014. The 2-year lag explains the difference in the number of observations

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

negative efficiency effect of female leaders is not statistically significant. The coefficient of the interaction term *Female*Network* increases in terms of magnitude by 20% (from 0.234 to 0.286) and confirms its positive effect on technical efficiency. Interestingly, a similar result applies for digital intensive sectors, where the negative effect of female leaders disappears. Albeit we stress the suggestive-only nature of this preliminary exploration, the results are in line with the view that, in contexts in which *soft skills* and the ability to work in teams are key capabilities, female senior roles are not detrimental for performance and that networking and female leadership are a good combination for improving firm efficiency. However, we cannot exclude, as a possible explanation, that innovative firms are simply more likely to hire and promote on the basis of talent alone, irrespective of arguments such as those implied by the "pipeline" and "backlash" hypotheses depicted above. Clearly, future research should continue to investigate the mediating role of digitization and technological advances in the firm-wide returns of female leadership and networking activities.

5.5 Controlling for the probability of networking and of having female leaders

The probability of entering a network agreement as well as of having a woman in leadership roles might depend on specific firms' present or past (observed or unobserved) characteristics, an issue that may introduce potential biases in the estimated effects. We try to partially mitigate this problem by applying a propensity score-based approach, proposed by Card and De La Rica (2006) on the base of the theoretical framework proposed by Imbens (2004). This approach requires estimating a first-stage model for the presence of network agreements as well as for the presence of female leaders preliminarily, using past observation of firms characteristics, relative to 2014 in our case. Therefore, a polynomial in the fitted probability (i.e., the propensity score for each firm) is included among the regressors in the truncated regression used to explain performances. This procedure allows to control in a flexible and parsimonious way for past observed and unobserved characteristics, which can influence the adoption of network agreements and the presence of female leaders.

Accordingly, we report the results from the inclusion of fitted probability, its squared and cubed terms among the explanatory variables in our usual baseline regression (Table 4, model 4) as well as in the specifications without interaction terms (Table 4, model 2). The results, reported in the first two columns of Table 7, somewhat confirm the robustness of our main findings on the negative effect from female representation and on the positive impact of female-leaded firms participating to networks. In comparison to our reference model (Table 4, Model 4), the estimated coefficient for networking is smaller, even if it remains non-significant, while the coefficient for *Female*Network* drops in value by 8.5%, a reduction in line with what reported by Card and De La Rica (2006) for their application. The other coefficients remain substantially stable, as is the case for the dummy indicating the female representation. The results are also very similar if we consider the comparison with the model without the interaction term (Table 4, model 2), and the main conclusion remains the same.

A similar procedure has also been applied for the presence of at least one female top leader, with the same approach and covariates used above. Also in this case, the results reported in columns 3–4 of Table 7 show that the inclusion of fitted probability terms reduces the estimated coefficients for the variables of interest and for the interaction with networking, but the main messages remain broadly unchanged.

6 Conclusion

Despite a recent, prolific, and heated debate on the effects of wider female participation to firms' high-level managerial decisions, something that is undoubtedly desirable from a social point of view, empirical results on the effects of this participation on a firm's economic and financial performance are rather inconclusive. A separate debate has emerged in recent years on the actual role of another key contributing factor to a firm's performance, i.e., engagement in firm networking activities. Even though the available empirical literature has produced a relatively stronger case for the alleged positive effects of networking, particularly for the performance of SMEs, here too, there remain substantial uncertainties on the real magnitude of the estimated effects. We have contributed to both debates by offering fresh empirical evidence based on a large-scale empirical analysis of manufacturing firms operating in Italy and on econometric tools from Data Envelope Analysis. We also add to the existing literatures by offering a first exploration of the way the two phenomena—female participation in leadership positions and a firm's engagement in networking activities with other firms—might interact with one another, producing new insights on the determinants of a firm's success in diverse economic environments.

Our findings suggest that, in general, DEA technical efficiency scores are negatively affected by a stronger presence of females among top leaders, while an opposite effect emerges in the presence of network agreements with other firms. The analysis also pointed out the existence of crucial interaction effects. Firstly, a firm's efficiency significantly increases when firms with female leaders participate to formal network agreements, hinting at a superior capacity of women to cooperate and to support successful teams, two aspects emerging from the field experiments conducted by Kuhn and Villeval (2015). Secondly, the presence of women in senior roles is no longer negative for a firm's efficiency when we focus on subsamples of firms operating in female intensive sectors, i.e., sectors where the share of females over the total number of employees is above average. This result suggests that females are not detrimental of performances "per se." Rather, they may encounter specific difficulties in organizational task, more often than their male counterparts, in the typical "male-dominated" environment of the manufacturing industry. Also, in line with the results reported by Flabbi et al. (2019) the presence of female leaders interacts positively with the share of female workers, with the annulment of the negative effect registered for the whole sample. Thirdly, within innovative or digital intensive sectors, the negative effect of female leaders disappears and the role of networks created among firms with females in senior roles increases, confirming how the negative effect of women leaders is specific for traditional and less dynamic environments.

Overall, we believe that these results may contribute to the important debate on female participation to the economy. For instance, our results suggest that stimulating the presence of females in top roles might be detrimental for performance only if the overall female participation to the workforce does not increase accordingly. Indeed, increasing the presence of female leaders in male intensive sectors might create potential discriminatory behaviors and organizational frictions limiting firms' performances in the short- and long-term, if this is not accompanied by broader stimuli aimed at increasing more generally the participation of women to all sectors in the economy. It is important, however, to highlight some potential limits of our work. First, our analysis focuses on the manufacturing sector, where, traditionally, women are under-represented both in leading positions and as employees. Second, we focus on a specific measure of performance, based on the DEA efficiency scores. Fruitful areas for future research may be found in the empirical analysis of the combined effects of female leaders and firm networking on a broader set of firm-level measures of economic and financial performance.

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Appendix. The Italian network contract

The Italian legislation introduced with Law Decree 5/2009 (converted into Law 33/2009), the *contratto di rete* (*network contract*). It allows different companies to "cooperate in order to increase, either individually and collectively their innovative capabilities and competitiveness in the market." The ambition of this legal instrument is to enhance the growth of SMEs. For these purposes, firms mutually agree to collaborate in predetermined forms and contexts on the base of a shared framework program regarding the management of their own companies, exchange industrial, commercial, technical, or technological information or services, or perform jointly one or more activities that are part of each company's corporate goals.

The flexible normative background is intentionally weak in terms of binding constraints. The only requirements rely on the definition of the strategic goals aimed to improve innovation capacity and market competitiveness, on the identification of activities and investments needed for the implementation of the strategic goals, and on the specification of rights and duties for each participant. Aspects, such as entry and exit rules, as well conditions for network resolution are determined by the parties, and the ownership of assets, rights, and obligations is respectively legally attributable to each single company. Further governance aspects of the business network agreement rely on the optional creation of a common fund and of a common body in charge of the management of the network. Legal subjectivity and resulting limited liability are elective only when the network provides for the creation of a common capital fund and establishes a separate legal entity.

As compared to other forms of networking, such as *informal networks* (other firms in the industry, family, and friends) and *weak formal networks* (industry associations, business consultants, or banks), the Italian *network contract* is an example of a *strong* and *formal network*, where clear objectives are stated and adhesion of members is explicit and based on the voluntary act of signing an agreement.

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