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Are entrepreneurial networks shaped by firms' organisational characteristics? A cross country comparison of the MENA region

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Abstract: This paper examines how network attributes are related to firms' organisational characteristics. The paper utilises Adult Population Survey (APS, 18–64) data for 15 countries. The sample descriptives show that, on the whole, the network environment differs across firm characteristics, but private networks dominate all characteristics. Latent class analysis results show that female entrepreneurs are significantly less likely to fall into any class, relative to class five, when compared to men. While some firm characteristics increase the odds of receiving advice from all sources (transforming type firms), others increase the odds of receiving advice from the private network environment only (business services and starting phase firms).

Keywords: entrepreneurship; firm organisational characteristics; network composition; latent class analysis; LCA.

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1 Introduction and review

This paper is concerned with networking and firms' organisational characteristics. The intention is to investigate whether particular patterns are distinguishable between network composition and firm characteristics. In particular, firms' most identifying characteristics are related (but not limited) to their size (which can be measured by the number of workers or capital stock), ownership, and age of the firm. At the theoretical level, the literature points to the importance of the firm's characteristics in shaping its networking behaviour. Indeed, some argue that a firm's network position or status has a direct impact on shaping the firm's boundary choices. Yang et al. (2010) and Shipilov (2006) postulate that network structure impacts the firm's boundary choices; however, less research has been devoted to investigating the impact of firm level characteristics and the firm's ability to benefit from its network positions. Yang et al. (2010) report that the firm's

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boundary choices are not independent of the surrounding network attributes. In particular, they propose that network density promotes partnering over non-partnering.

The literature on the boundary choices of firms follows two distinct tracks. The first is known as 'the resource-based view' which focuses on the firm's internal resource endowments (Barney, 1991), and the second is the social network track which emphasises the external resource opportunities (Podolny and Page, 1998; Uzzi, 1996). A third track, in an attempt to bridge the first two views (Yang et al., 2010; Lavie, 2006), proposes a multilevel framework of firm boundary choices. The argument about how network composition benefits the entrepreneur goes in two directions: the first relates to the structural holes network (Burt, 2000), which implies an open non-redundant network that provides diverse information. The second is referred to as the closure argument (Anderson et al., 2005), which argues that the closed network provides trust within the network that acts as a binding relationship among entrepreneurs. Gulati et al. (2002) focus on organisational networks, their formation and firm performance. Another paper that ascertains the importance of networks in shaping the intent to become an entrepreneur is Klyver and Schøtt (2011). Their paper bridges the disconnect between the intention literature and that of the network literature.

Although the literature on networks and firm boundary choices is vast, few studies have addressed how entrepreneurs' networks relate to firms' organisational characteristics. This paper reviews the relationship between each of the firm's characteristics and networks classified by their environment (private, work, market, professional, and international), which are analysed in a descriptive manner. Subsequently, a different classification of latent classes based on their manifestations is suggested, and then the determinants of belonging to the highest probability class are analysed using multinomial logit regression. This approach has been used in the literature (Van Der Gaag and Snijders, 2005) for classifying social networks. This study utilises a sample of 13,251 entrepreneurs across 15 countries[1] between 2009 and 2011. The data time coverage of all countries is not uniform, so making intertemporal comparisons is not possible.

The paper is organised as follows: Section 2 presents a description of network composition and firm characteristics, followed by the section on empirical analysis and hypothesis testing. Section 4 concludes with recommendations.

2 Network composition and firm characteristics

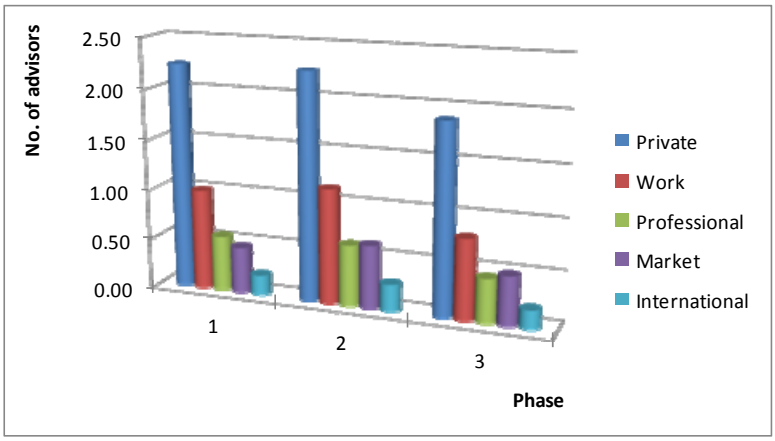
This section provides an overview of the relationship between network composition[2] and each of the firms' organisational characteristics. The APS national level data were consolidated into a single data set for the 15 countries. The surveys were conducted during the years 2009–2011. The timeframe, however, is not unified for all countries making any cross-country comparisons subject to changes in the indicators over time. The variables were harmonised to maintain a certain level of comparability. The national level data were used to describe the main variables of interest (firm characteristics) and networking variables. The expanded data file includes variables on networking and summarises the network composition in five categories: private, market, professional, work, and international. The classification of the network compositions into these groups has different implications vis-à-vis firm characteristics. For example, it is expected that firms in large open economies are more likely to have international environment

networking while small closed economies tend to have a more private environment type of structure.

2.1 Network composition and phase

The phase of a firm refers to the phase of entrepreneurship; the first phase refers to prospective entrepreneurs, while the other two are starting up (2) and operating (3) phases. It is expected that the phase of entrepreneurship reflects the general relationship in terms of reliance on family and friend networks.

Figure 1 Mean number of advisors by phase and network type (see online version for colours)



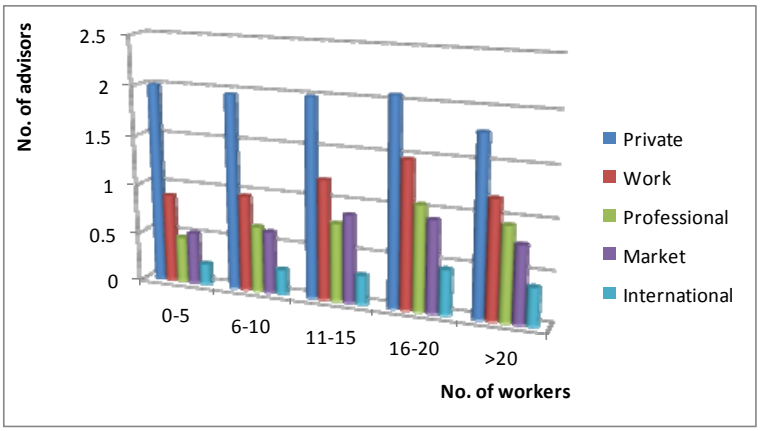
It is evident that the starting phase (2) displays a higher number of advisors for each type of network. However, as firms move into the operating phase (3), their reliance on networks of all kinds diminishes even when compared to prospective (1) entrepreneurs.

2.2 Network composition and size

The size of a firm can be measured by the number of workers. As firm size is a choice variable for firms in the long run, so is the size and type of network. As larger firms tend to benefit from their scale of operations, it is also expected that firms' boundaries will be expanded. Harvie et al. (2010) found that engagement in production networks enables SMEs to exploit competitiveness emanating from economies of scale. Figure 2 shows this relationship.

The evidence presented in Figure 2 shows several trends: first, once again, the private network dominates all sizes of firm in varying degrees. The second observation is that the work, professional, and market environments all form an inverted u shape. Finally, the international environment seems to increase with size. It is worth noting that firms with up to 20 workers constitute 97% of the sample, which has important implications. In particular, a positive relationship between the number of advisors and firm size exists for the work, professional, and market networks.

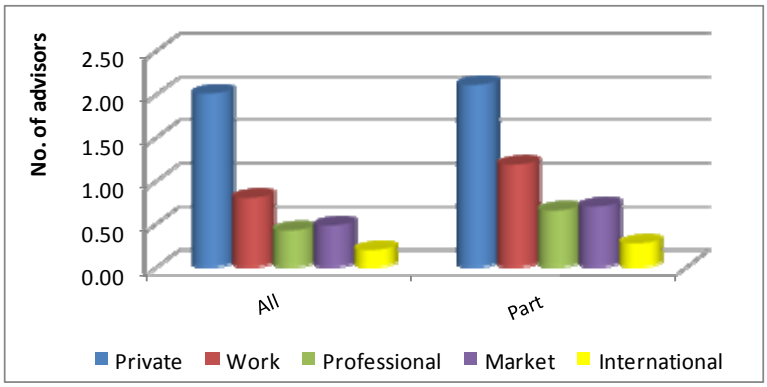
Figure 2 Mean number of advisors by network type and firm size (see online version for colours)



2.3 Network composition and ownership

The APS asks entrepreneurs whether they are the sole owner (ALL) of the business or whether they are co-owners (Part) of the business. The distribution in Figure 3 shows the 5% confidence interval of the mean number of advisors. It is evident that the distribution of network composition for each type of ownership is quite similar.

Figure 3 The mean number of advisors by network type and ownership (see online version for colours)



On the other hand, comparing sole ownership with part ownership shows significant differences. One could say that although the private network environment has the highest number of advisors for both types of ownership, partial ownership has a significantly higher number of advisors for the work and market networks. This also turns out to be the case for the rest of the categories. It is important to note that this result may be attributable to the different counts for each type of network in the sole and part ownership types; it happens to be the case that the number of advisors in each type of network for 'all' is nearly twice that of 'part'.

2.4 Network composition and firm age

As firms grow older, their experience in managing and coping with various aspects of the risks associated with shocks also grows. This indicates that firm age may be negatively correlated with the number of advisors. On the other hand, the networking activities of established firms are expected to be larger because they are in the market for a longer period. The question is, does firm age necessitate a certain and different type of network from that of a starting or young firm? A scatter-plot of firm age and the mean number of advisors is provided in Figure 4; as expected, younger firms tend to capitalise on a larger number of advisors possibly due to their lack of experience.

Figure 4 Mean number of advisors and firm age (years) (see online version for colours)

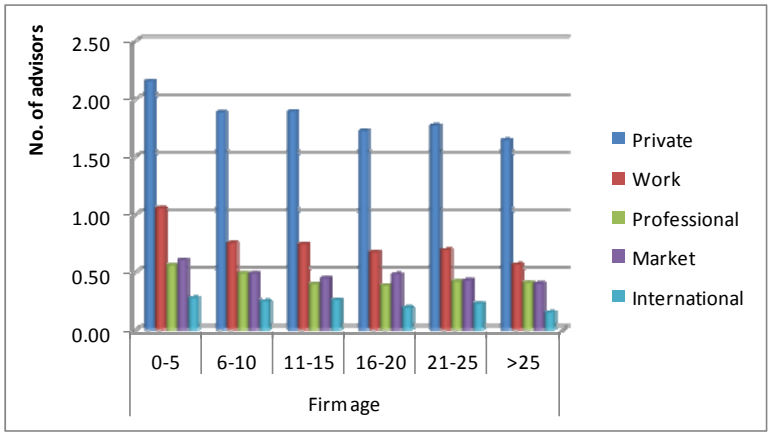


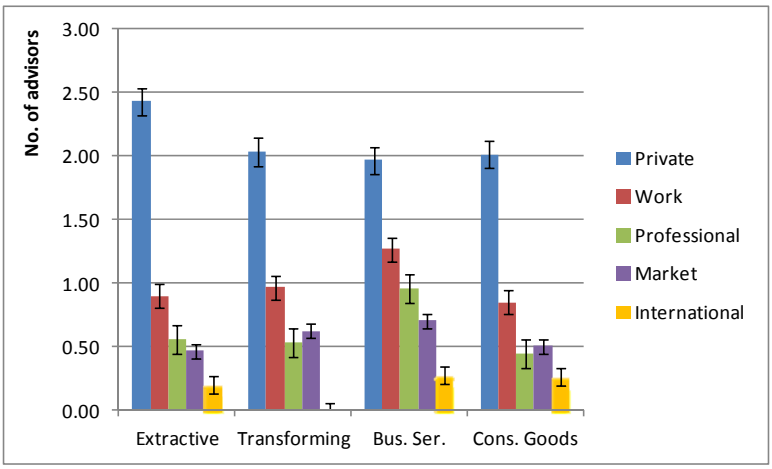
Figure 4 shows that the private network declines with firm age; additionally, the number of advisors also declines, on average, for the work environment. Other types of networks show a drop for firms aged 6 to 10 years of age compared with young firms of 0 to 5 years. Network composition does not vary with firm age. The private network dominates all age groups, followed by work, then professional and market, and finally international.

In respect of the network type, the data report very little variation across the network types for any particular firm age group. In fact, the figures are almost constant for each country under each firm age group. However, differences across countries are found; for example, Tunisia has the smallest number of advisors for the 0 to 5 years age group (43) and the highest number of advisors for the more than 25 years age group (10). Therefore, one cannot say that larger firms tend to be more likely to have a professional network or to have a larger number of professional advisors across all countries. No trends are distinguishable.

2.5 Network composition and firm type

The type of firm refers to its Standard Industrial Classification (SIC), which groups firms by the type of activity they engage in. The kind of network environment for consumer goods may, or may not, be similar to that of business services. This remains an empirical question. The grouping of responses by firm type and network environment is in Figure 5.

Figure 5 Mean number of advisors by firm type (see online version for colours)

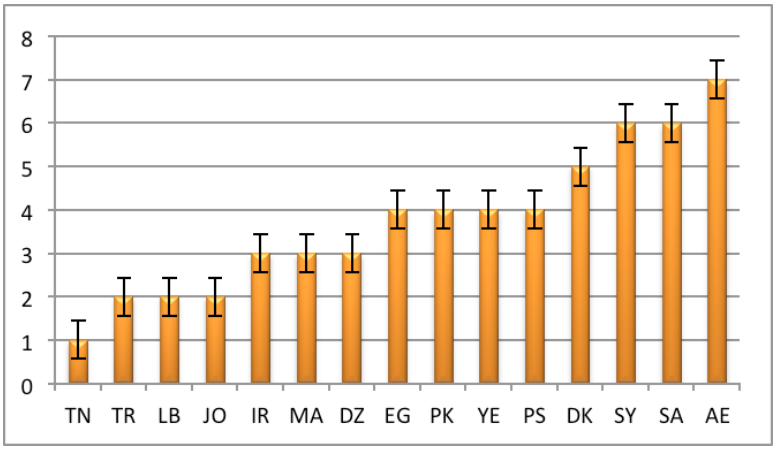


The average number of private network advisors is very strongly present in extractive firm types; although it is also present in other firm types, the ratio diminishes for business services and transforming industries. Compared to other firm types, business services seem to have more market, work, and professional advisors.

3 Empirical analyses with test of hypotheses

To investigate the main networking indicator 'total number of advisors' across countries, Figure 6 provides the median number of networks per firm across countries. If networking is important to firm survival, then discontinuation is expected to be high in Tunisia compared to the other countries, unless financing and profitability outweigh the negative effect of networking.

Figure 6 median numbers of advisors in total in a network (see online version for colours)



Note: See footnote 1 for country abbreviations.

Figure 6 displays the median number of total network advisors in each country; this figure has the property of being at the centre of a frequency distribution. As such the representative firm in Denmark has received advice from five different resources. The error bars indicate that there are significant differences between blocks of countries; this implies that Tunisia is significantly lower than any other country. On the other hand, using Denmark as a benchmark, only Saudi Arabia, Syria and UAE have a higher total number of network advisors. Clusters do seem to exist; however, the differences between clusters seem to be significant due to the non-overlapping of their confidence intervals.

3.1 Networking decision

This section investigates the effect of firm characteristics on networking decisions. The latent class analysis (LCA) is first employed to assign a latent class number to each of the firms. This is then used as a dependent variable in a multinomial logit regression with firm characteristics as explanatory variables, along with other control variables. The use of LCA is primarily to predict network class membership.[3] The number of latent classes is determined based on a set of categorical manifestations. Although the latent classes are not observed, they are classified based on observed categorical variables, which are assumed to be independent. The number of latent classes is usually set based on some information criteria (IC). Nylund et al. (2007) point out that there is no single statistical indicator that is commonly accepted for deciding the number of latent classes; however, they find that the Baysian IC and bootstrap likelihood ratio test perform best. LCA estimates are based on maximum likelihood estimation of conditional response probabilities; in other words, a latent class will have a particular value given that the manifest variable has a particular value. Dayton (1998) points out that maximum likelihood estimation are calculated before the allocation of cases to latent classes; for more information on the computation of posterior Bayesian probabilities, see Dayton (1998). Although LCA is the categorical equivalent of factor analysis, using factor analysis may give misleading parameter estimates and goodness of fit estimates (Vermont and Magidson, 2000). The latent class model is a probability model (Goodman (1974); suppose two manifestations (a, b) of a latent variable x are observed, then

$$\pi_{xab} = \pi_x \pi_{ax} \pi_{bx} \tag{1}$$

where π_x and π_{ax} and π_{bx} are the latent probability, and conditional response probabilities respectively. This study uses 20 manifestations as explained above. The sample counts and proportions are shown in Table 1.

It is evident that few entrepreneurs have received advice from any of the network classes except for the private environment. This has implications for the distribution of class membership assignment; Figure 7 shows the classification of individuals based on maximum likelihood estimation. The figure shows that class 4 has the highest number of entrepreneurs (34.4%). The LO-MENDELL-RUBIN adjusted likelihood ratio test of the null, that there are only four classes as opposed to the alternative of 5, is 1,304, which is significant at high levels. Further investigation shows that the cross tabulation of latent classes and each of the five network environments resulted in a rejection of the null hypothesis of no relationship. Furthermore, Figure 7(a) shows distinctive patterns for the number of advisors and class type (the likelihood ratio test of no relation is significant). Panel A plots cases in each class, which have a total number of advisors of a certain size

disregarding the frequency. Panel B shows the total number of advisors in each class disregarding the size. It is obvious that class 1 (with a penchant for taking advice) has a concentration near the top of the scale, although Figure 7(b) shows a lower number of total advisors for class 1 than all other cases. Class 4 has the highest number in terms of frequency (panel B), but the figure shows they are all concentrated near the bottom of the scale. Furthermore, classes 3 and 5 are similar, but three have higher frequencies within that range.

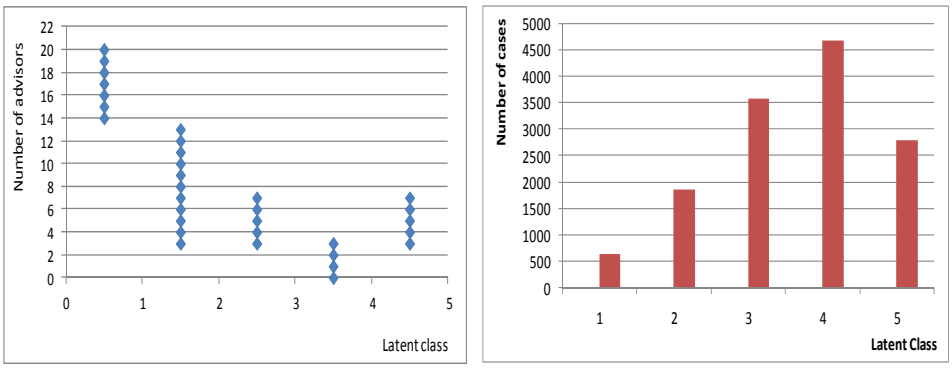
Table 1 Sample counts and proportions of receiving advice from various network classes

Class	*Manifest*	*Code**	*Proportion*	*Class*	*Manifest*	*Code**	*Proportion*
Private	Spouse	1	0.56	Professional	Bank	1	0.92
		2	0.44			2	0.08
	Parent	1	0.42		Lawyer	1	0.91
		2	0.58			2	0.09
	Family	1	0.43		Accountant	1	0.88
		2	0.57			2	0.12
	Friend	1	0.42		Advisor	1	0.90
		2	0.58			2	0.10
Workplace	Work colleague	1	0.68	Market	Collaborator	1	0.87
		2	0.32			2	0.13
	Boss	1	0.87		Competitor	1	0.93
		2	0.14			2	0.07
	Starter	1	0.77		Supplier	1	0.86
		2	0.23			2	0.14
	Experienced business	1	0.66		Customer	1	0.79
		2	0.34			2	0.21
Professional	Researcher	1	0.92	International	Someone living abroad	1	0.89
		2	0.08			2	0.11
	Investor	1	0.89		Someone who came from abroad	1	0.90
		2	0.11			2	0.11

Notes: *1: refers to having not received advice from those listed, 2: refers to advice being received.

What does this mean in terms of networking and classes? The classification was based on whether or not entrepreneurs receive advice as well as where from. Class 1 which always likes to receive advice is a minority among entrepreneurs, but their penchant for receiving advice is reflected in the high number of advisors. On the other hand, class 4 is prevalent, but since they do not like receiving advice, the number of advisors is small. There is another set of entrepreneurs who receive advice only from the private network; for these the number of advisors covers a wide range. The striking result is that if classes 2, 3, 4, and 5 are put together, we can see that the vast majority (95.2%) do not receive advice (at least from work, professional, market and international networks).

Figure 7 (a) The distribution of total number of advisors by latent class (b) Classification of entrepreneurs based on their most likely latent class membership (see online version for colours)



(a) (b)

Since each person has a probability of being in all five latent classes, one can take the average probability for all those who are classified as being within any class. This information is shown in Table 2; as expected, the figures show that the diagonal elements have the highest average probabilities with class 4 having the highest average. Thus the mean probability of those classified in class 1 is 81.3%; however, the mean probability of a class 1 assignment being in class 2 is only 14%.

Table 2 Average latent class probabilities for most likely latent class membership (row) by latent class (column)

	1	*2*	*3*	*4*	*5*
1	*0.813*	0.140	0.039	0.000	0.008
2	0.025	*0.860*	0.111	0.002	0.002
3	0.021	0.112	*0.757*	0.049	0.061
4	0.000	0.002	0.041	*0.896*	0.061
5	0.021	0.034	0.117	0.088	*0.741*

The threshold values (not reported) are the expected values of latent classes at which the manifest variables change from category 1 (have not received advice) to category 2 (have received advice). The highest probability of cases falling into class 4 and being classified in class 4 is 89.6%. The results in Table 3 are the results in a probability scale where $P_{ij} = 1 / (1 + e^{Tij})$ where T_{ij} is the threshold value for category i and class j. These can be used to get an understanding of what the classes are; for example, there is a 0% chance that someone has received advice from an investor being classified in class 5, but a 100% chance for someone who has not received advice from an investor of being classified in class 5. The following is a general characterisation of classes:

- class 1, always receives advice
- class 2, receives advice from private networks only

- class 3, does not receive advice from professional, market, or international networks, but has a weak preference to receive some advice from a parent, other family or a friend
- class 4 does not receive advice from anyone
- class 5, is another copy of 3 but with a stronger preference not to receive advice (like 4), and stronger preference than 3 to receive advice from private networks.

3.2 Determinants of networking decision

This section investigates the determinants of class assignment (the highest probability of belonging to a particular class) using the multinomial logit model. Palestinian entrepreneurs can choose between class 1 (j = 1), class 2 (j = 2), class 3 (j = 3), class 4 (j = 4), or class 5 (j = 5). The base category (j = 5) is the base outcome group, which includes 'receives advice from private networks only'. The probability of selecting sector j is,

$$P_j = \frac{e^{z\alpha_j}}{1+\sum_j e^{z\alpha_j}} \tag{2}$$

Equation (2) is estimated by the multinomial logit method in SPSS. The vector z includes gender, total number of advisors, and all firm characteristics. The results are shown in Table 3.

Table 3 Multinomial logit regression results, dependent variable latent class

	Class 1[a]		*Class 2*[a]		*Class 3*[a]		*Class 4*[a]	
	Coeff.	*P-value*	*Coeff.*	*P-value*	*Coeff.*	*P-value*	*Coeff.*	*P-value*
Intercept	–1.96	*0.00*	0.24	0.12	0.75	*0.00*	1.06	*0.00*
Firm size	0.01	0.13	0.01	0.13	0.01	0.24	0.01	0.32
Firm age	–0.02	0.33	0.00	0.85	–0.02	*0.04*	0.01	0.11
Starting phase[b]	–0.29	0.43	0.22	0.13	0.27	*0.04*	–0.12	0.33
Sole owner[b]	–0.61	*0.05*	–0.53	*0.00*	–0.29	*0.01*	–0.04	0.71
Female[b]	–1.43	*0.00*	–0.59	*0.00*	–0.37	*0.00*	0.29	*0.01*
[Gender male = 1]	0[b]	-	0[b]	-	0[b]	-	0[b]	-
Firm type[b]-exchange	0.17	0.72	–0.15	0.41	–0.29	0.08	–0.62	*0.00*
Transforming	0.91	*0.01*	0.19	0.22	0.01	0.92	–0.11	0.39
Business services	0.63	0.20	0.78	*0.00*	0.26	0.15	–0.40	*0.03*

Notes: [a]the base category is class 5
[b]base categories are: male, consumer goods, prospective, partnership.

The results indicate that latent class 4 is the most prevalent, constituting 38.3% of all the cases; approximately 73% of the cases are male, 20% are in transforming type activity, 56% are in the operating phase, and 64% are sole owners. The model fitting information

shows a $\chi^2_{30} = 233.7$ which is significant at high levels, implying that at least one of the coefficients is not zero. The pseudo R-squared values (Cox and Snell, Nagelkerke, and McFadden) range between 0.024 and 0.068, which is relatively low. Parameter estimates are the multinomial odds of belonging to any class relative to class 5. Females and sole owners are less likely to belong to class 1 relative to class 5, while male entrepreneurs and part owners are more likely to receive advice. On the other hand, entrepreneurs in transforming industries are more likely not to receive advice than those who are involved in consumer goods activities. Females, extractive type firms, and business services type firms are less likely to fall into class 4 (does not like to take advice from anyone) relative to class 5 (who seem to take advice from private and work environment networks). Females are consistently less likely to belong to any class (compared to males) relative to class 5. More often than not, the most significant variables have a negative sign implying the entrepreneurs' likelihood of receiving advice from private or work networks (see Figure 7). The odds ratios (not reported) for females compared to males are all less than one; this implies that they are more likely than males to fall within class 5. Firm age is only significant in class 3 with a negative sign; this means that older firms are less likely to fall into class 3 relative to class 5, implying a stronger preference for receiving advice from private sources.

4 Conclusions and recommendations

This research addresses the relationship between the firms' network attributes and their organisational characteristics. The network attributes are classified into five categories, in two different ways. *The first* is entirely based on the environment (space) of the network from private (family related) to international (whether at home or abroad). This classification focuses on the number of advisors in each type of the network environment variables. The analysis based on this classification is thus descriptive in nature and relates each of the network environment measures to each of the firm characteristics. The results overwhelmingly show that the mean number of advisors in the private network environment exceeds other kinds for all firms of different attributes. This result is obvious in Figure 1 (phase of operation); however, firms in the operating phase seem to rely less heavily on advisors than prospective and starting phase firms. In respect to size (see Figure 2), reliance on the private network environment declines, while the work, professional, market and international environments gain more importance as size increases. This indicates that larger firms tend to utilise their competitive benefits more when their networks are more diversified. In each type of network environment, sole ownership has a lower average number of advisors when compared with partnerships. The differences are starker in work, professional, and market environments. This is despite the fact that the sample shows almost twice as many cases in sole ownership as in partnerships for each network type. The quality of finance index varies negatively with the average number of advisors. Entrepreneurs who rely heavily on a private network have the lowest quality of finance index; whilst for professional networks, the index is highest. This leads to the conclusion that improving the quality of finance may improve firm performance, as the advice from the professional network is more tied to firm performance than advice from the private network (which may be mostly support). Firm age (experience) seems to reduce the need for reliance on network advisors; this points to

the need to support those in the prospective and starting phases with increased networking activities. Finally, firms in business services activities rely more heavily on work, professional, and market networks than do other types of firms.

The second classification of networks was based on 20 network questions using the LCA; each of the yes/no questions asked the entrepreneur if she/he has received advice last year from any of the 20 possibilities. The sample counts show that for each one of the five network environments, the proportion of entrepreneurs who have not received advice is always more than one half (except for private networks). What this implies is that more often than not, entrepreneurs do not take advice and that self-reliance is more the rule than the exception. Figure 7(b) shows that class 4 (which does not receive advice from anyone) accounts for roughly 40% of the sample. The results of the multinomial logit regression show that some variables (firm size) are not significant in determining class choice, whether to receive advice or not and from whom. Other factors such as gender are always significant, indicating that females are less likely than males to be classified in any class relative to class 5 (which favours advice from private networks). The remaining variables are significant for some classes and not significant for others. When they are significant, they tend to be negative except for firms in the starting phase. When compared to prospective entrepreneurs, they are more likely to fall into classes 2 and 3 relative to class 5. This implies that such firms are weakly geared to receive advice from private networks and less likely to not receive advice at all. This also applies to firms in transforming activities in class 1 and business services in class 2.

Based on the findings above, a few recommendations can be made based on the assumption that networking is beneficial to firms' performance. First, it was found that the vast majority of entrepreneurs do not receive advice and when they do, it is more likely to be from private sources. Therefore, increasing the awareness of the benefits of networking is necessary. If it was the case that the low participation in networking activities was due to the cost of networking, then more effective ways of networking are needed. This recommendation requires more research in this area to be done. Second, throughout the paper, it was shown that networking and firm characteristics are not entirely independent and that the relationship is not robust. For example, only gender was always significant in explaining the assignment to any particular class. As a matter of fact, women are more likely than men to only receive advice from private networks. Finally, the high number of advisors in the private class for each type of network environment should not divert our attention from the low frequency in that category. In essence, private networking may be most suitable for moral support, but not necessarily the most effective in terms of performance enhancement.

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Notes

1 The countries are: Algeria (DZ), Denmark (DK), Egypt (EG), Iran (IR), Jordan (JO), Lebanon (LB), Morocco (MA), Pakistan (PK), Palestine (PS), Saudi Arabia (SA), Syria (SY), Tunisia (TN), Turkey (TR), United Arab Emirates (AE), and Yemen (YE).

2 The set of categorical variables can be classified into five classes:

- a private network (spouse, parent, other family, friend)
- b work environment network (co-worker, boss, someone who started a business last year, someone with business experience)
- c professional environment network (researcher, investor, banker, lawyer, accountant, business public advisor)
- d market environment network (collaborating firm, competitor, supplier, customer)
- e international environment network (living abroad, has been abroad).

3 In contrast to factor analysis, LCA is used for categorical variables and does not assume normality.