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## Do People Know Who Knows? Evidence from Advice Networks

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# Do People Know Who Knows? Evidence from Advice Networks

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**Abstract**

Do people seek advice from objectively more knowledgeable peers? I study this question using network data from a survey experiment ($N = 1{,}162$), linked to university administrative records and a public graduation registry. Respondents named advice contacts and hangout contacts, allowing me to compare advice-seeking ties with ordinary social ties in the same environment. Respondents with higher financial and economic literacy receive disproportionately more advice nominations than hangout nominations. A similar advice-hangout pattern appears for graduation status among registry-matched contacts. Within the same respondent's network, advice contacts are also more literate and more likely to have graduated than hangout contacts. The advice-hangout literacy difference is largest among lower-literacy respondents. The results suggest that advice networks reveal expertise recognition beyond ordinary social proximity.

**JEL codes:** D83, D85, I23, C93
**Keywords:** advice networks; expertise; financial literacy; social networks; Argentina

## 1 Introduction

People often rely on others when making decisions under limited information. Whether this improves decisions depends not only on the presence of knowledgeable peers, but also on whether individuals know whom to ask for advice (Golub and Jackson, 2010). I study whether the peers named for advice score higher on researcher-observed measures of knowledge than peers named in ordinary social ties.

Network research in economics shows that social structure shapes learning, information aggregation, and diffusion (Jackson et al., 2017; Conley and Udry, 2010; Banerjee et al., 2019; Beaman et al., 2021). Closest to this paper, Derksen and Souza (2026) show that experimentally expanding information access increases students' centrality as peers form information-sharing links. A related advice-network literature emphasizes expertise recognition: people seek information from contacts when they know what those contacts know, value that knowledge, and can access them at reasonable cost (Borgatti and Cross, 2003). Cross and Sproull (2004) show that advice relationships provide actionable knowledge and that source expertise predicts the usefulness of these relationships. I complement this literature by comparing advice nominations with hangout nominations in the same peer environment using objectively measured literacy and graduation status.

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I study this question using data from a survey experiment conducted among students and alumni of the School of Economic Sciences at Universidad Nacional del Nordeste in Argentina (Marino Fages, 2026) merged with administrative data from the university. Respondents listed up to five people they go to for advice and up to five people they hang out with the most. I match named contacts to survey respondents with measured financial and economic literacy and to public graduate registry records. The registry measure is especially useful because it is available for named contacts who did not answer the survey, expanding the target sample and reducing selection from conditioning only on survey respondents. The key empirical comparison is between advice ties and hangout ties. If advice nominations mainly capture generic popularity or social proximity, knowledge should predict advice and hangout nominations similarly. If they reveal expertise recognition, the knowledge gradient should be stronger for advice.

The main result is that knowledgeable respondents are disproportionately named for advice. A similar pattern appears for graduation status in the registry-matched target frame: among contacts and respondents who can be linked to graduation records, graduation is more strongly associated with advice nominations than with hangout nominations. The within-respondent comparison shows that this pattern is not only a target-level nomination pattern: holding fixed stable characteristics of the respondent, the same respondent's advice contacts are more literate and more likely to have graduated than that respondent's hangout contacts. Heterogeneity by respondent literacy differs across the two measures: the advice-hangout literacy gap is largest among lower-literacy respondents, while the advice-hangout graduation gap is larger among higher-literacy respondents.

This paper contributes to the economics literature on networks and information diffusion by showing that advice-seeking choices are systematically related to peers' objectively measured literacy. Existing work shows that networks shape information transmission and that nominations can identify central spreaders. By benchmarking advice ties against hangout ties in the same peer environment, I show that advice nominations contain information about objectively measured expertise beyond ordinary social proximity. This matters for information campaigns because targeting requires knowing not only who is central in the social network, but also whom people consult when they seek advice.

## 2 Data and Network Construction

The data come from an online survey experiment conducted among students and alumni of the School of Economic Sciences at Universidad Nacional del Nordeste (Marino Fages, 2026).[1] The main degree programs are Accounting, Business Administration, Economics, Labor Relations, and Foreign Trade. The survey contains 1,162 respondents and includes demographics, administrative records, financial and economic literacy, and beliefs about current macroeconomic indicators.[2]

The sample provides a heterogeneous university-linked population: public universities in Argentina charge no tuition and admission is not binding in practice, generating broad early enroll-

[1] The experiment was programmed in Qualtrics and approved by Durham University's Ethics Committee under `DUBS-2023-09-20T11_53_32-zqlr86`.

[2] The literacy score is survey-based: correct answers to nine economic/monetary, financial, and numeracy questions, from 0 to 9.

ment. In the administrative roster, recent cohorts average about 1,700 entrants per year, and the survey covers students and alumni from different cohorts, including dropouts. The university also imposes no limit on the number of years they can take to graduate.

Respondents listed up to five people they go to for advice and up to five people they hang out with the most.[3] I match named contacts to survey respondents, producing a matched respondent-to-respondent network with 1,154 distinct directed dyads in the union of the two network layers. Layer-specific counts are 778 advice edges and 754 hangout edges, with some dyads appearing in both layers. Because characteristics are observed only for survey respondents, the analysis of contact literacy uses nominations that can be matched to another respondent. Advice and hangout nominations are similarly likely to point to survey respondents: 18.4 percent of registry-matched advice nominations and 17.9 percent of registry-matched hangout nominations are to co-respondents.

The main target characteristics are economic and financial literacy and graduation status. The literacy score is available for survey respondents (see Marino Fages, 2026, for a detailed description of the sample). I also match named contacts to a public graduate registry using national id numbers and define a contact as graduated if the registry contains a graduation record dated before October 2023. This registry match extends the target-level analysis beyond survey respondents to a larger and more representative set of named contacts.

## 3 Empirical Specification

I use two complementary analyses. The target-centered analysis asks whether more literate or graduated targets receive more nominations. The respondent-centered analysis asks whether the same respondent names contacts with stronger expertise markers for advice than for hangout.

The target-centered specification compares whether the same individual characteristic predicts incoming advice and hangout nominations:

$$Y_{i\ell} = \alpha + \beta X_i + \delta(X_i \times H_\ell) + \rho H_\ell + \Gamma' W_i + \varepsilon_{i\ell}, \tag{1}$$

where $\ell \in \{\text{advice}, \text{hangout}\}$ indexes the network layer. $Y_{i\ell}$ is the number of respondents who nominate target $i$ in layer $\ell$, $H_\ell$ is an indicator for the hangout layer, and $X_i$ is either standardized literacy or an indicator for whether the target had graduated before October 2023. Controls $W_i$ include gender, province, degree program, and university entry cohort; the literacy regressions also control for age. The coefficient $\beta$ is the advice-network gradient. Since $H_\ell = 1$ for hangout, the hangout-network gradient is $\beta + \delta$. In the tables, I report the advice-minus-hangout difference, $\beta - (\beta + \delta) = -\delta$, so positive values indicate that the target characteristic predicts advice nominations more strongly than hangout nominations. Standard errors are clustered by target in stacked target-layer models.

The respondent-centered specification is a within-respondent comparison. For each respondent who names at least one matched advice contact and one matched hangout contact, I compare the

[3] The advice question did not refer to any particular domain, but after answering questions on forecasts of economic indicators, respondents may have been primed to think about economic advice.

average characteristics of the two sets of targets. I estimate

$$\bar{Z}_{i\ell} = \alpha_i + \theta A_\ell + u_{i\ell}, \tag{2}$$

where $\bar{Z}_{i\ell}$ is the mean characteristic (see Table 2) of the matched contacts named by respondent $i$ in layer $\ell$, $\alpha_i$ is a respondent fixed effect, and $A_\ell$ is an indicator for the advice layer. The coefficient $\theta$ is the within-respondent advice-hangout difference. It shows whether a respondent's advice contacts have higher literacy scores than that same respondent's hangout contacts, removing stable respondent-level differences in general sociability, attention, and willingness to list names.

I explore heterogeneity by estimating equation (2) separately by respondent-literacy group.

# 4 Results

Table 1 studies recognition by the network. It shows that literacy predicts nominations in both networks, but more strongly in the advice network. For scale, the mean advice in-degree in the literacy sample is 0.734, and the estimated literacy gradient corresponds to about 31 percent of this mean. The corresponding hangout gradient is smaller, and the advice-hangout difference is significant at the one percent level. Because nominations are skewed and many respondents receive none, I also report log(1 + in-degree), which downweights highly nominated respondents, and an indicator for receiving any nomination, which isolates whether knowledgeable respondents are named at all. These two specifications check that the result is not only a count difference driven by a small number of frequently named respondents. Both measures point in the same direction: the literacy gradient is larger for advice than for hangout nominations.[4] Panel B shows a similar pattern using graduation status from the registry. This measure is valuable because it can be observed for named contacts matched by national id number who did not answer the survey, increasing the sample size and making the target-level evidence less dependent on survey response. Targets who graduated before October 2023 receive more nominations, and this gradient is larger for advice than for hangout.[5] Appendix Table 4 shows that the count and log-count results are robust to interacting all controls with the hangout-network indicator.

Table 1 answers a target-level question: are more knowledgeable respondents more likely to be named by others? That result does not by itself show that individual respondents distinguish between advice and ordinary social contacts. Table 2 therefore shifts the comparison to the respondent and asks whether the same respondent names more literate people for advice than for hangout. Panel A shows that advice contacts answer 0.163 more literacy questions correctly than hangout contacts on average. Advice contacts are also 4.5 percentage points more likely to be more literate than the respondent who named them. Panel B repeats the within-respondent comparison using the broader registry-matched sample. Advice contacts are 3.7 percentage points more likely than hangout contacts to have graduated before October 2023. Advice and hangout contacts look

[4] A current-value accuracy index based on distance from correct exchange-rate, inflation, and unemployment values gives consistent results.

[5] Restricting the graduation analysis to cohorts entering in 2018 or earlier, who had more time to graduate by 2023, gives similar advice-hangout differences.

Table 1: Target characteristics and incoming network nominations

| | Mean dep. var. | Advice | Hangout | Advice − Hangout |
|---|---|---|---|---|
| *Panel A. Literacy score* | | | | |
| Count in-degree | 0.734 / 0.699 | 0.228*** | 0.125*** | 0.103*** |
| | | (0.044) | (0.040) | (0.030) |
| $\log(1 + \text{in-degree})$ | 0.357 / 0.363 | 0.107*** | 0.071*** | 0.036*** |
| | | (0.018) | (0.018) | (0.012) |
| Any nomination | 0.349 / 0.367 | 0.100*** | 0.072*** | 0.028** |
| | | (0.015) | (0.016) | (0.013) |
| *Panel B. Graduated before October 2023* | | | | |
| Count in-degree | 1.223 / 1.190 | 0.462** | 0.096 | 0.367*** |
| | | (0.193) | (0.177) | (0.088) |
| $\log(1 + \text{in-degree})$ | 0.614 / 0.626 | 0.126*** | -0.018 | 0.144*** |
| | | (0.040) | (0.039) | (0.036) |
| Any nomination | 0.664 / 0.690 | 0.085*** | -0.029 | 0.114*** |
| | | (0.028) | (0.030) | (0.041) |

Notes: Each row reports a stacked advice-hangout regression. The mean dependent variable column reports advice/hangout means in the estimation sample. Literacy is standardized. Graduated before October 2023 is an indicator equal to one if the target appears in the graduate registry with a graduation date before October 2023. Panel A uses matched respondent targets and controls for target age, gender, province, degree program, and university entry cohort. Panel B uses targets matched by national id number, including named nonrespondents, and controls for target gender, province, degree program, and university entry cohort. Standard errors, clustered by target, are in parentheses. The number of person-network observations is 1,880 in Panel A and 4,476 in Panel B. The last coefficient column reports the advice-minus-hangout difference. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

similar in gender, province, and entry cohort, while advice contacts are slightly less likely to be from the same degree program.

Appendix Table 3 further separates overlapping and non-overlapping ties among matched respondent-to-respondent dyads. Advice-only contacts are more literate than hangout-only contacts. In a dyad-level regression with respondent fixed effects, advice-only contacts answer 0.49 more literacy questions correctly than hangout-only contacts. Contacts named in both networks are not statistically different from hangout-only contacts. This indicates that respondents do not merely turn to more literate contacts within their hangout network; they also name more literate contacts who are outside that network.

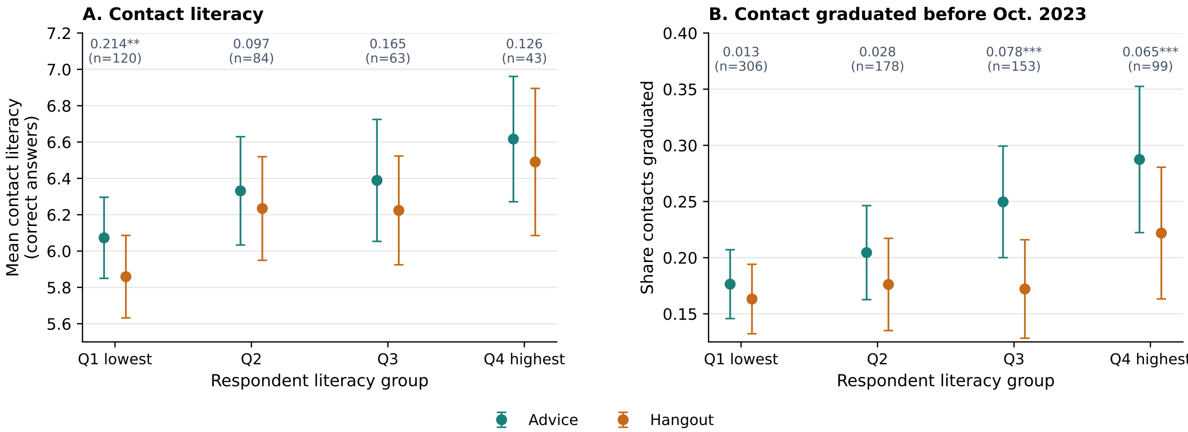
Table 2: Within-respondent comparison of advice and hangout contacts

| Target characteristic | Advice − Hangout | S.E. | Obs. | Nominators |
|---|---|---|---|---|
| *Panel A. Literacy among matched survey respondents* | | | | |
| Target literacy | 0.163** | 0.071 | 634 | 317 |
| Target more literate than respondent | 0.045** | 0.021 | 620 | 310 |
| Same gender | -0.010 | 0.027 | 618 | 309 |
| Same province | -0.014 | 0.027 | 670 | 335 |
| Same degree program | -0.038 | 0.026 | 680 | 340 |
| Same entry cohort | 0.000 | 0.024 | 680 | 340 |
| *Panel B. Graduation and composition among registry-matched contacts* | | | | |
| Target graduated before October 2023 | 0.037*** | 0.014 | 1,492 | 746 |
| Same gender | -0.017 | 0.017 | 1,378 | 689 |
| Same province | -0.016 | 0.016 | 1,422 | 711 |
| Same degree program | -0.034** | 0.016 | 1,442 | 721 |
| Same entry cohort | -0.014 | 0.012 | 1,446 | 723 |

Notes: Each row reports equation (2). The coefficient is the advice-minus-hangout difference in the mean characteristic of matched contacts named by the same respondent. Panel A uses contacts matched to survey respondents; literacy is measured as the number of correct answers out of nine. The target-more-literate row is defined only when both the respondent and the contact have observed literacy. Panel B uses contacts matched by national id number to the graduate registry and administrative roster. Nominators are respondents with at least one matched advice contact and one matched hangout contact for the row. Regressions include respondent fixed effects. Standard errors, clustered by respondent, are reported in the S.E. column. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure 1 explores heterogeneity by respondent literacy. Panel A shows that the advice-hangout literacy difference is largest among respondents in the lowest literacy group: their advice contacts answer 0.214 more literacy questions correctly than their hangout contacts. Panel B shows a different pattern for graduation status: the advice-hangout difference is positive in all groups but larger and statistically distinguishable from zero in the upper half of the literacy distribution. Both panels also show knowledge homophily, with higher-literacy respondents naming more literate and more often graduated contacts.

Figure 1: Advice and hangout contacts by respondent literacy group




*Notes:* The figure reports within-respondent comparisons by respondent-literacy group. Points show the average characteristics of advice and hangout contacts, computed within respondent and then averaged within group. Literacy groups are defined from the observed values of the discrete 0–9 literacy score: Q1 includes observed scores 1–5, Q2 score 6, Q3 score 7, and Q4 scores 8–9. Because the score is discrete, groups are not equal-sized. Panel A reports contact literacy in correct answers out of nine. Panel B reports the share of contacts who graduated before October 2023. Bars are 95 percent confidence intervals for the advice and hangout means. Numbers above each group report the paired advice-hangout difference; parentheses report the number of respondents with at least one matched advice contact and one matched hangout contact for that panel.

# 5 Discussion

I study whether respondents are able to identify knowledgeable peers in a real social environment. The evidence shows that advice ties point to more literate peers than hangout ties, and the within-respondent comparison shows that this pattern remains when comparing the same respondent's advice and hangout networks. Graduation provides a complementary result: advice contacts are also more likely to have graduated, a more visible marker of expertise. Together, the two measures suggest that advice ties contain information about expertise rather than only reflecting ordinary social proximity.

The heterogeneity results differ across the two markers of knowledge. Lower-literacy respondents display a more marked difference between the literacy of those whom they seek advice from and those whom they hang out with. In contrast, higher-literacy respondents display a clearer advice-hangout difference in graduation status. This distinction matters because the people who may benefit most from informal advice need not show the same advice-hangout patterns as those with higher baseline knowledge.

Four qualifications are worth noting. First, the analysis uses partially observed target characteristics: literacy is observed only when a named person also answered the survey and can be uniquely matched. The graduate registry partly mitigates this issue by recovering graduation status for a broader set of named contacts matched by national id number, including nonrespondents. Second, advice seeking is self-reported. Incentivised measures of actual advice seeking would be useful, but respondents had no obvious reason to misstate whom they consult, and the main comparison uses the same elicitation format for advice and hangout ties. Third, literacy and graduation do not capture every dimension of expertise. They may also be correlated with broader ability or diligence. I also do not observe the content of advice, so the results speak to expertise recognition rather than to whether advice from more literate or graduated contacts is ultimately more useful. In this setting, however, they are substantively relevant because the sample comes from an economics school and the survey centered on economic forecasts, which may have primed respondents to think about financial and economic advice. Finally, the evidence comes from one university-linked community in northeastern Argentina, so external validity to other populations and settings remains open.

# A Additional Results

Table 3: Literacy by overlapping and non-overlapping network ties

| Tie type | Mean target literacy | Respondent FE coefficient | Obs. |
|---|---|---|---|
| Hangout only | 6.045 | omitted | 335 |
| Both advice and hangout | 6.227 | 0.108 | 348 |
| | | (0.253) | |
| Advice only | 6.407 | 0.491** | 366 |
| | | (0.215) | |

Notes: The table uses matched respondent-to-respondent dyads with observed target literacy. Target literacy is the number of correct answers out of nine. The respondent fixed-effect coefficients come from a dyad-level regression of target literacy on tie type, with hangout-only ties as the omitted category and respondent fixed effects. Standard errors are clustered by respondent. The fixed-effect model uses 1,049 dyads from 589 respondents. ** $p < 0.05$.

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# Declaration of Generative AI and AI-Assisted Technologies

During the preparation of this draft, the author used AI-assisted writing tools to organize prior empirical results and produce an initial LaTeX draft. The author reviewed and edited the content and takes full responsibility for the final manuscript.

Table 4: Robustness: Interacting controls with network type

| | Mean dep. var. | Advice | Hangout | Advice − Hangout |
|---|---|---|---|---|
| *Panel A. Literacy score* | | | | |
| Count in-degree | 0.734 / 0.699 | 0.223*** | 0.130*** | 0.093*** |
| | | (0.044) | (0.041) | (0.032) |
| $\log(1 + \text{in-degree})$ | 0.357 / 0.363 | 0.105*** | 0.073*** | 0.033** |
| | | (0.018) | (0.018) | (0.013) |
| Any nomination | 0.349 / 0.367 | 0.098*** | 0.075*** | 0.023 |
| | | (0.016) | (0.017) | (0.015) |
| *Panel B. Graduated before October 2023* | | | | |
| Count in-degree | 1.223 / 1.190 | 0.425** | 0.133 | 0.292*** |
| | | (0.195) | (0.177) | (0.093) |
| $\log(1 + \text{in-degree})$ | 0.614 / 0.626 | 0.113*** | -0.004 | 0.117*** |
| | | (0.041) | (0.039) | (0.038) |
| Any nomination | 0.664 / 0.690 | 0.073** | -0.017 | 0.091** |
| | | (0.029) | (0.031) | (0.043) |

Notes: This table repeats Table 1 after interacting all controls with the hangout-network indicator. Panel A controls for target age, gender, province, degree program, and university entry cohort, each interacted with network type. Panel B controls for target gender, province, degree program, and university entry cohort, each interacted with network type. Standard errors, clustered by target, are in parentheses. The number of person-network observations is 1,880 in Panel A and 4,476 in Panel B. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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