

The Embeddedness Gradient: Social Composition of Crowd Capital and Venture Outcomes in Reward Crowdfunding

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Abstract

Research on entrepreneurial finance focuses overwhelmingly on *how much* capital founders raise, treating a dollar as a dollar. We argue that, in reward crowdfunding, the social composition of capital—*who* the money comes from—is associated with a venture’s later trajectory in ways the amount raised cannot capture. Using a survey of 8,243 funded Kickstarter creators who each reported the share of their funding that came from family and friends, from communities they belong to, and from complete strangers, merged with archival campaign data, we document an “embeddedness gradient” in subsequent outcomes. Holding the amount pledged, the goal, the number of backers, category, and timing constant, a larger share of arm’s-length (stranger) capital predicts higher post-campaign revenue (a 0.066 \log_{10} change per +10 percentage points, implying roughly a 16% revenue difference per 10 points and about 4.6 \times across the full range), and modestly higher rates of serial founding, professional follow-on (VC or angel) investment, and external recognition. Company formation is positive but non-significant under our preferred pre-treatment specification ($p = 0.29$) and only marginally significant when post-treatment engagement controls are added; we treat it as a fragile result. Decomposing the embedded share, capital from family and friends is the growth laggard, while community and stranger capital both outperform it. Direct equality tests between community and stranger shares show only marginally significant differences (Wald p in the 0.07–0.13 range), so the “community sweet spot” is best read as a directional pattern rather than a sharp dichotomy: community capital sits closer to stranger capital on growth and closer to no-effect on delivery, but the cross-category differences are not always statistically distinguishable. Revenue is robust across the full battery of checks. Serial founding is robust across most checks—CEM, Oster bounds ($\delta = 3.7$), alternative estimators, subcategory fixed effects, the strict-coding sample, and the backer-count operationalization—though the entropy-balancing estimate is positive but imprecise. Company-formation and delivery results are more fragile. Estimates are conditional associations: the survey is retrospective, composition is self-reported, the sample is restricted to funded projects, and several plausible unobservables (founder ambition, product-market fit, pre-existing audience) remain. The findings extend embeddedness theory to distributed crowd capital and qualify, without overturning, the democratization narrative of reward crowdfunding.

Keywords: crowdfunding; crowd capital; embeddedness; social capital; entrepreneurial finance; venture growth; project delivery

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1 Introduction

Where a venture’s money comes from has long been understood to matter as much as how much it raises. A dollar from a venture capitalist arrives bundled with governance, networks, and a public signal of quality (Hsu, 2004; Stuart et al., 1999); a dollar from a founder’s parents arrives bundled with goodwill and patience but little independent validation (Robb and Robinson, 2014). Yet most empirical work on entrepreneurial finance—and nearly all work on crowdfunding—measures funding as a scalar: the amount raised, or whether a goal was met (Mollick, 2014; Agrawal et al., 2014). This paper asks a different question. When thousands of small backers collectively finance a project, the resulting pool of “crowd capital” is socially heterogeneous: some comes from the founder’s family and friends, some from communities the founder already belongs to, and some from complete strangers reached through the market. Does this composition—holding the amount constant—predict what the venture becomes?

We argue that it does, for theoretically grounded reasons. Drawing on the sociology of markets and organizations (Granovetter, 1985; Uzzi, 1997; Nahapiet and Ghoshal, 1998), we treat the share of funding raised at arm’s length from strangers as a measure of genuine market validation, and the share raised from embedded relationships (family, friends, and communities) as a measure of relational capital. The two do different work. Strangers who back a project despite no prior relationship reveal information: their willingness to pay is a credible, decentralized signal of broad demand (Spence, 1973; Connelly et al., 2011) that can be parlayed into firm formation, professional investment, and growth (Roma et al., 2017; Kerr et al., 2014). Embedded backers, in contrast, supply commitment and accountability: trust, patience, and ongoing social ties that support a creator’s central obligation—delivering the promised product—but that carry little market information and may flow to projects that could not attract a wider audience (Coleman, 1988; Uzzi, 1997).

Crowdfunding is an unusually clean setting in which to study composition, because the crowd is observable and decomposable. We use a large survey of Kickstarter creators—merged with archival campaign data—in which each funded creator reported the percentage of their backers, and of their dollars, that came from family and friends, from communities they belong to, and from strangers. This yields a direct, project-level measure of the social composition of crowd capital that is unavailable in conventional finance data and, to our knowledge, has not previously been linked to venture outcomes.

Our results document an *embeddedness gradient* in conditional associations. First, arm’s-length capital predicts scaling: net of the amount raised, the goal, the number of backers, category, and timing, a +10-percentage-point increase in stranger funding is associated with about 16% higher post-campaign revenue (and roughly $4.6\times$ across the full 0–100 percentage-point range), modestly higher probabilities of launching another project (1.6 pp), of earning press or awards (1.0 pp), and of attracting venture or angel follow-on (0.6 pp). Company formation is positive but not statistically significant under our preferred pre-treatment specification and we treat it as

fragile. Second, decomposing the embedded category, funding from family and friends is the growth laggard; both community and stranger capital outperform it. Community capital sits directionally above stranger capital on delivery and slightly below it on growth—a pattern consistent with the embeddedness “sweet spot” predicted by the paradox of embeddedness (Uzzi, 1997; Burt, 2004; Granovetter, 1973)—but direct Wald tests show the community-vs-stranger differences are only marginally significant (Wald p in the 0.07–0.13 range across outcomes). We therefore read the gradient as a directional pattern rather than a sharp four-cell typology. Third, the relative payoff to arm’s-length capital depends on scale: in larger campaigns, a higher stranger share is significantly associated with greater company formation; the parallel scale-contingent delivery cost is directionally consistent but does not reach conventional significance.

These findings contribute to three literatures. To social-capital and embeddedness research (Coleman, 1988; Nahapiet and Ghoshal, 1998; Adler and Kwon, 2002), we extend a framework developed for dyadic and network ties to the distributed, partially anonymous setting of the crowd, and we show that the embeddedness paradox reappears in the composition of a funding base. To entrepreneurial finance, we show that the informational content of capital—not only its quantity—predicts which projects become growing firms, complementing signaling accounts of investment (Stuart et al., 1999; Roma et al., 2017). To crowdfunding research specifically, we qualify the influential claim that the model “democratizes” access to capital (Mollick, 2014; Agrawal et al., 2015; Sorenson et al., 2016): democratized access to money does not imply democratized access to growth, because projects financed largely by friends and family—precisely the founders for whom crowdfunding is supposed to substitute for absent market access—are the least likely to scale.

2 Theory and Hypotheses

2.1 Crowd capital as socially composed

Crowdfunding lets entrepreneurs raise money from many individuals, each contributing a small amount, typically in exchange for a product or experience rather than equity (Mollick, 2014; Belleflamme et al., 2014). The literature has largely treated the crowd as an aggregate—total dollars, number of backers, success or failure—and asked what campaign features attract it (Mollick, 2014; Kuppuswamy and Bayus, 2017; Courtney et al., 2017). A parallel stream studies how a founder’s pre-existing social capital seeds early contributions (Colombo et al., 2015; Agrawal et al., 2015). We build on both but shift the question from *how much* a founder raises to the *social composition* of what is raised.

Following economic sociology, we distinguish ties by their embeddedness: the degree to which an exchange is enmeshed in ongoing social relationships rather than conducted at arm’s length (Granovetter, 1985; Uzzi, 1996). A funding base can be arrayed along this dimension: strong-tie capital from family and friends; weaker but still embedded capital from communities the founder belongs to; and arm’s-length capital from strangers reached through the platform’s market. Embeddedness

theory holds that these locations differ systematically in the resources they convey—information versus trust, reach versus solidarity (Granovetter, 1973; Coleman, 1988; Burt, 1992; Adler and Kwon, 2002)—which leads us to expect them to predict different venture outcomes.

2.2 Arm’s-length capital and market validation

Strangers have no relational reason to fund a project. When they nonetheless pay, their willingness to pay is informative in a way that embedded contributions are not: it constitutes a credible, decentralized signal of broad demand (Spence, 1973; Connelly et al., 2011; Mollick and Nanda, 2016). This signal has an external and an internal function. Externally, a demonstrated willingness of unrelated consumers to pay de-risks the venture for downstream resource holders—professional investors, distributors, and employees—who can read the campaign as a market test (Kerr et al., 2014; Roma et al., 2017; Courtney et al., 2017). Consistent with this logic, reward-based campaign performance has been shown to attract subsequent professional investment (Roma et al., 2017), and third-party endorsements more generally accelerate resource acquisition by young ventures (Stuart et al., 1999; Hsu, 2004). Internally, broad stranger demand expands the venture’s addressable market beyond the founder’s personal network, making growth feasible rather than parochial. We therefore expect arm’s-length composition, net of the amount raised, to predict scaling.

H1 (market validation). The greater the share of a project’s funding that comes from strangers (arm’s-length capital), the more the venture subsequently scales—higher revenue, firm formation, professional follow-on investment, serial founding, and external recognition.

2.3 Embedded capital: two competing predictions

What should we expect from embedded funding? The literature supports two predictions that disagree about *which* embedded ties matter and how.

The first, simpler, prediction extends a long tradition treating embedded ties as a uniform resource. Embedded backers—family, friends, and community members alike—supply trust, fine-grained information transfer, and joint problem solving that arm’s-length ties cannot (Uzzi, 1997; Nahapiet and Ghoshal, 1998; Coleman, 1988). They can monitor the creator through ongoing relationships, extend patience when delivery slips, and provide non-financial help (Colombo et al., 2015; Seghers et al., 2012). Read naively, this implies that any embedded composition—high family share, high community share, or both—should support delivery and satisfaction.

H2 (uniform embedded benefit). The greater the share of a project’s funding from embedded ties (family, friends, or communities), the more likely the creator is to deliver, deliver on time, and satisfy backers.

A second, more nuanced prediction follows from the embeddedness *paradox* (Uzzi, 1997), weak-ties theory (Granovetter, 1973), and brokerage (Burt, 2004). These literatures argue that the benefits of embeddedness are non-monotonic: some embeddedness furnishes trust and information, but too much insulates an actor from outside information, talent, and demand. Applied to a funding base, this predicts a *gradient* rather than a uniform embedded advantage. Family-and-friends capital is maximally embedded and minimally informative: such backers fund the *founder*, not the market, and can sustain projects with no broader demand. Community capital occupies an intermediate position—embedded enough to confer accountability, yet weak and numerous enough to carry market-like information and to reach beyond the founder’s intimate circle. Arm’s-length stranger capital sits at the low-embeddedness extreme: maximally informative but minimally accountable. The implication is that community capital—not embedded capital broadly—should occupy a sweet spot.

H3 (embeddedness gradient, competing with H2). The association between embeddedness and venture outcomes is graded: strong-tie family-and-friends capital underperforms both community and arm’s-length capital on scaling, while community capital, more than family-and-friends capital, supports on-time delivery and backer-rated success.

H2 and H3 are competing rather than nested. H2 treats embedded as a single category; H3 partitions it. The empirical decomposition in Section 5.3 adjudicates between them by entering community and stranger shares separately with family-and-friends as the reference, and by directly testing the equality of community and stranger coefficients.

2.4 Scale as a contingency

If embedded ties matter for delivery because they furnish relational accountability, and arm’s-length capital matters for growth because it conveys market validation, both effects should be most consequential in large, ambitious projects. Small campaigns impose limited execution demands and produce small ventures regardless of composition; large campaigns impose complex delivery obligations on creators who often lack managerial infrastructure (heightening the value of relational monitoring) and present larger growth opportunities to ventures that have demonstrated market demand (heightening the value of stranger validation) (Uzzi, 1997; Kerr et al., 2014). We therefore expect scale to amplify the asymmetric pattern documented under H1–H3: relative to embedded capital, arm’s-length capital should look even better on growth and worse on delivery in larger projects.

H4 (scale contingency). In larger, higher-stakes campaigns, the relative scaling advantage of arm’s-length capital widens, and any relative delivery disadvantage relative to embedded capital becomes more apparent.

3 Data and Measures

3.1 Setting and sample

Our data combine a large survey of Kickstarter project creators with archival data on their campaigns drawn from the platform. The survey asked creators about the composition of their backers, their delivery and post-campaign trajectory, and their venture and career outcomes; it was merged to administrative records of goal, amount pledged, backers, category, launch date, and engagement (updates and comments). A parallel survey of backers provides the backer-rated success and satisfaction outcomes used in some specifications. We restrict the analytic sample to funded projects that raised at least \$1,000 and that have non-missing data on the social composition of funding, yielding 8,243 creators. All monetary values are converted to U.S. dollars. The main models include category and launch-year fixed effects; the bivariate columns of the specification ladder in Section 5.1 do not, by construction.

3.2 Measuring the composition of crowd capital

Each creator reported the percentage of the funds pledged to their project that came from (i) family and friends, (ii) members of online or real-world communities they belong to, and (iii) complete strangers. We normalize the three percentages to sum to one within each project; an omitted category is treated as zero. Our primary independent variable is the *stranger (arm's-length) share*; because the three shares sum to one, the embedded share equals one minus the stranger share. In decomposition models we enter the community and stranger shares with family as the reference category. As a robustness check we replace the dollar-weighted shares with the analogous shares of the backer count. On average, family and friends supplied 51% of dollars, communities 24%, and strangers 25% (Table 12).

Measurement validity. Three features support the measure. First, among respondents answering at least one component, the three percentages sum to 100 ± 5 for 73% of projects (median exactly 100), indicating that creators treated them as an exhaustive partition. Second, the dollar-weighted and backer-count versions of each share are very highly correlated (stranger share $r = 0.95$; family share $r = 0.94$), evidence of convergent validity across two independently asked questions. Third, the stranger share varies systematically and sensibly across categories—highest in Technology (0.59), Product Design (0.56), and Games (0.53), and lowest in Theater & Dance (0.10) and Music (0.12)—and rises with project size, motivating the category and size controls described below.

3.3 Outcomes

Scaling. Post-campaign revenue (a 12-category scale converted to dollar midpoints and logged); an indicator for any post-campaign revenue; an indicator for forming a company (a formal corporate entity rather than an individual or informal group); an indicator for obtaining follow-on venture-capital or angel funding after the campaign; an indicator for the creator launching another project (serial founding); and an indicator for external recognition (press coverage, awards, or going viral).

Delivery and satisfaction. An indicator for having delivered the project; an indicator for on-time delivery; the creator’s self-rated delivery; backers’ mean ratings that the project was a success and that they were satisfied (from a parallel survey of the projects’ backers); and an indicator that backers deemed the project a failure.

3.4 Controls and the pre- vs. post-treatment distinction

Our preferred (*pre-treatment*) control set includes the (log) amount pledged, the (log) goal, the (log) number of backers, an indicator for a pitch video, a U.S. indicator, and category and launch-year fixed effects. Controlling for the amount pledged and the number of backers is essential: it ensures that the composition coefficients capture *who* funded the project, not how much was raised or how many people participated. We exclude the log of the pledged-to-goal ratio because it equals $\log(\text{pledged}) - \log(\text{goal})$ and is perfectly collinear with the two terms we already include. (The *raw* pledged-to-goal ratio is not perfectly collinear, but the log form—the more common formulation in this literature—is.) Demographic controls (creator gender, age, and college education), available for the subset of solo creators, are added in robustness checks.

We also report results with (log) updates and (log) comments added as additional controls. These campaign-engagement variables are plausibly post-treatment: a campaign attracting strangers may, for that reason, accumulate more updates and comments. Conditioning on them may absorb part of the mechanism (mediator bias) or open a path through colliders. We therefore use the pre-treatment specification as primary and report the engagement-controlled specification as robustness. Coefficients are nearly identical across the two (Table 8), suggesting that the engagement controls neither rescue nor explain away the headline results.

4 Empirical Strategy

We estimate linear models with heteroskedasticity-robust standard errors (clustered by creator where creators contribute multiple observations) and category and launch-year fixed effects. For binary outcomes we report linear probability models, following the convention in this literature and to avoid the incidental-parameters and separation problems that arise when many fixed-effect dummies are combined with logit; we confirm below that average marginal effects from logit are nearly identical. Because composition is not randomly assigned, we complement the regressions with

Table 1: Specification ladder: post-campaign revenue and the arm’s-length funding share.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Stranger share ($\times 10\text{pp}$)	+0.1696*** (0.0075)	+0.0724*** (0.0084)	+0.0744*** (0.0085)	+0.0674*** (0.0092)	+0.0658*** (0.0091)	+0.0663*** (0.0094)	+0.0653*** (0.0110)
Size controls (pledged, goal, backers)		Yes	Yes	Yes	Yes	Yes	Yes
Video + US controls			Yes	Yes	Yes	Yes	Yes
Category fixed effects				Yes	Yes	Yes	Yes
Year fixed effects					Yes	Yes	Yes
Engagement (updates, comments) [post-treatment]						Yes	
Demographics (female, age, college)							Yes
R^2	0.066	0.140	0.140	0.221	0.235	0.235	0.218
N	7,282	7,282	7,282	7,282	7,282	7,282	4,811

Dependent variable is \log_{10} post-campaign revenue. The coefficient is the change per +10 percentage points of stranger (arm’s-length) standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

three identification checks: (i) coarsened exact matching (Iacus et al., 2012), comparing projects above and below the median stranger share within strata exactly matched on category, year, product type, and quintiles of goal, pledged amount, and backers; (ii) entropy balancing (Hainmueller, 2012), which reweights to equate covariate means; and (iii) Oster (2019) coefficient-stability bounds, which gauge how strong selection on unobservables would have to be, relative to selection on the rich observables, to nullify a result. We frame our estimates as conditional associations: the survey is retrospective and the design cannot fully rule out reverse causality, a limitation we revisit in Section 7.

5 Results

5.1 Arm’s-length capital and scaling (H1)

Table 1 traces the revenue association across a specification ladder using pre-treatment controls (column 5 is our primary specification). The bivariate coefficient on the stranger share (0.170 per ten points) falls to 0.072 once we control for project size and to 0.066 with the full set of pre-treatment controls and category and year fixed effects, where it stabilizes; adding post-treatment engagement controls (column 6) leaves it at 0.066, and adding demographics (column 7) leaves it at 0.065. The stability of the coefficient after size and category absorption—it moves trivially as R^2 rises from 0.14 to 0.24—is consistent with stranger share capturing something distinct from project size, though it does not rule out unobserved confounders correlated with composition but uncorrelated with the observables.

Table 2 extends this to the full slate of scaling outcomes, reporting both the primary pre-treatment specification and the engagement-controlled robustness in the same table. Under the pre-treatment specification, a +10-point change in the stranger share is associated with a 0.066 increase in \log_{10} revenue ($p < 0.001$). Per ten points this implies a $10^{0.066} - 1 \approx 16\%$ revenue difference; across the full range from all-embedded to all-stranger funding it implies a $10^{0.66} \approx 4.6\times$ difference, holding the amount raised constant. The same shift is associated with a 1.6-point higher

Table 2: Arm’s-length (stranger) funding share and venture scaling.

	Log revenue	Any revenue	Formed company	VC/angel	Serial	Press/award
<i>Primary: pre-treatment controls</i>						
Stranger share ($\times 10pp$)	+0.0658*** (0.0091)	+0.0160*** (0.0023)	+0.0025 (0.0024)	+0.0062*** (0.0022)	+0.0158*** (0.0022)	+0.0104*** (0.0023)
R^2	0.235	0.157	0.135	0.050	0.062	0.099
N	7,282	7,282	8,234	4,492	8,211	8,243
<i>Robustness: + post-treatment engagement (updates, comments)</i>						
Stranger share ($\times 10pp$)	+0.0663*** (0.0094)	+0.0153*** (0.0024)	+0.0046* (0.0024)	+0.0056** (0.0022)	+0.0139*** (0.0023)	+0.0123*** (0.0024)
R^2	0.235	0.159	0.137	0.051	0.065	0.102
N	7,282	7,282	8,234	4,492	8,211	8,243

Each column is a separate regression; log revenue is OLS, binary outcomes are linear probability models. Standard errors clustered by creator. All models include the (log) amount pledged, (log) goal, (log) backers, a video indicator, a U.S. indicator, (log) updates and comments, and category and launch-year fixed effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

probability of any post-campaign revenue ($p < 0.001$), a 1.6-point higher probability of launching another project ($p < 0.001$), a 1.0-point higher probability of press or awards ($p < 0.001$), and a 0.6-point higher probability of venture or angel follow-on ($p < 0.01$). Company formation is positive ($b = +0.0025$) but not statistically significant under the pre-treatment specification ($p = 0.29$); adding post-treatment engagement controls pulls the coefficient up to $b = +0.0046$ ($p = 0.06$), and the Oster bound for this outcome is $\delta = 0.58$, so we treat it as a fragile result not fully supported by H1. A more substantively meaningful contrast for the supported outcomes is the interquartile shift: moving from the 25th to the 75th percentile of stranger share (approximately a 39-point change) implies about a 60% revenue difference and a 6 percentage-point change in the probability of launching another project. Figure 1 displays these coefficients alongside the delivery coefficients of the next subsection. H1 is supported on revenue, serial founding, recognition, and follow-on funding; company formation is too fragile to support a confident H1 claim.

5.2 Delivery and satisfaction (H2)

Table 3 turns to delivery. Although the unconditional correlation between stranger funding and on-time delivery is negative (Appendix Table 13), much of it is accounted for by project size and category. Under the primary pre-treatment specification, two outcomes show small *marginally negative* effects: on-time delivery ($b = -0.005$, $p = 0.06$) and backer-rated success ($b = -0.010$, $p = 0.09$). Backer satisfaction, scope change, being deemed a failure, and having delivered at all are all statistically null. Adding the post-treatment engagement controls (log updates, log comments) pulls the on-time and backer-success coefficients toward zero ($b = -0.000$, $p = 0.93$ and $b = -0.003$, $p = 0.58$) and produces the well-known small positive “delivered at all” coefficient ($b = +0.004$, $p = 0.04$). Because updates and comments are themselves plausibly outcomes of attracting strangers, the post-treatment-controlled estimates likely absorb part of the relational-accountability mechanism rather than identifying it; we report both but lean on the pre-treatment

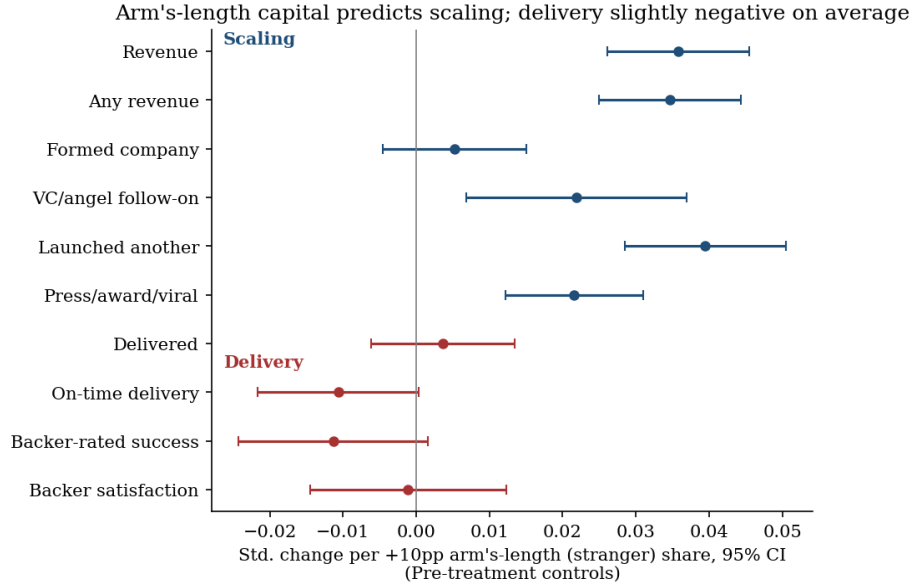


Figure 1: Associations of the arm’s-length (stranger) funding share with scaling (blue) and delivery (red) outcomes, per +10 percentage-point shift, with 95% confidence intervals under the primary pre-treatment specification. Each coefficient is the raw regression coefficient divided by the standard deviation of the outcome, so the axis is in outcome-SD units per +10pp. Scaling outcomes are positive, with most significant at conventional levels (company formation is not significant under pre-treatment controls and is treated as fragile). Delivery outcomes cluster near zero, with marginal negatives on on-time delivery ($p = 0.06$) and backer-rated success ($p = 0.09$).

numbers.

The takeaway is that the blanket version of H2—that arm’s-length capital uniformly improves or uniformly worsens delivery—is not supported: the average effects are small and at most marginally significant. As the decomposition and contingency analyses show, the more interesting structure is below the average: a delivery advantage specific to *community* (not family) capital, and a scale-dependent pattern for stranger capital.

5.3 The embeddedness gradient and the community sweet spot (H2 vs. H3)

Table 5 decomposes embeddedness by entering the community and stranger shares with family and friends as the reference category. The pattern is consistent with H3 over H2. Relative to family-and-friends capital, both community and stranger capital are associated with substantially more revenue, more company formation, and more serial founding (all $p < 0.01$): the scaling “penalty” of embeddedness is really the penalty of *strong-tie*, kin-based capital, not embeddedness broadly. H2’s prediction that embedded composition uniformly supports delivery fails: family-and-friends share is the reference, and stranger share—the least embedded—is not negatively associated with delivery on average, whereas the embedded categories diverge from one another.

Table 3: Arm’s-length (stranger) funding share and delivery / satisfaction.

	Delivered	On time	Backer success	Backer satisf.	Deemed failure	Scope changed
<i>Primary: pre-treatment controls</i>						
Stranger share ($\times 10pp$)	+0.0013 (0.0018)	-0.0053* (0.0028)	-0.0096* (0.0056)	-0.0009 (0.0055)	+0.0005 (0.0013)	+0.0086 (0.0064)
R^2	0.126	0.067	0.038	0.049	0.015	0.039
N	8,226	6,876	4,185	3,957	4,344	8,217
<i>Robustness: + post-treatment engagement (updates, comments)</i>						
Stranger share ($\times 10pp$)	+0.0039** (0.0019)	-0.0002 (0.0029)	-0.0032 (0.0057)	+0.0031 (0.0055)	+0.0001 (0.0013)	-0.0006 (0.0065)
R^2	0.131	0.073	0.046	0.054	0.017	0.043
N	8,226	6,876	4,185	3,957	4,344	8,217

Backer-rated outcomes are from a parallel survey of the projects’ backers. All models include the (log) amount pledged, (log) goal, (log) backers, a video indicator, a U.S. indicator, (log) updates and comments, and category and launch-year fixed effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Are community and stranger different from each other? The decomposition’s clearest finding is that family-and-friends underperforms both, but the popular framing of a “community sweet spot” requires the stronger claim that community capital is also distinct from stranger capital—higher on delivery, lower or equal on growth. Table 4 reports Wald tests of equality between the community and stranger coefficients in the same regressions, the appropriate test of distinctness. The directional pattern goes the way H3 predicts in every cell: community sits above stranger on on-time delivery ($\Delta = -0.006$, community higher), backer-rated success ($\Delta = -0.013$, community higher), and company formation ($\Delta = -0.005$, community higher), and below stranger on VC/angel follow-on ($\Delta = +0.005$, stranger higher) and revenue ($\Delta = +0.017$, stranger higher). But the differences are only marginally significant. Wald p -values are 0.07 (backer-rated success), 0.07 (company formation), 0.09 (VC/angel), 0.11 (on-time), 0.13 (revenue), and 0.57 (serial founding). The most defensible reading is therefore that family-and-friends underperforms both, while community and stranger capital differ *directionally* in the way H3 predicts but rarely *cross-statistically*: community shows the pattern of relational accountability, stranger shows the pattern of market validation, but a strict significance test of community = stranger fails to reject equality at the 0.05 level for any outcome we examine.

Visualizing the gradient. Figure 2 shows the covariate-adjusted means by dominant funder type. Family-dominated projects lag on revenue; community-dominated projects sit close to stranger-dominated projects on growth and slightly above them on delivery. The figure reinforces the directional “sweet spot” pattern but should be read in light of the Wald evidence: H3’s gradient prediction is consistent with the data, but the community-vs-stranger gap is suggestive rather than sharp.

Table 4: Wald tests of community = stranger coefficients.

Outcome	Community ($\times 10\text{pp}$)	Stranger ($\times 10\text{pp}$)	Stranger–Community	Wald p
Log revenue	+0.0704***	+0.0872***	+0.0168 (0.0112)	0.132
Formed company	+0.0140***	+0.0087***	−0.0053 (0.0030)	0.073*
Serial founding	+0.0175***	+0.0191***	+0.0016 (0.0028)	0.571
VC/angel follow-on	+0.0014	+0.0059***	+0.0045 (0.0027)	0.091*
On-time delivery	+0.0074***	+0.0019	−0.0056 (0.0035)	0.109
Backer-rated success	+0.0159**	+0.0031	−0.0128 (0.0070)	0.066*

Each row is the same regression as in Table 5, with community and stranger shares (per +10 percentage points) entered together and family-and-friends share omitted as the reference. The Wald column reports the test that the community and stranger coefficients are equal. Standard errors clustered by creator.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Decomposition: community and stranger shares relative to family and friends.

	Log revenue	Formed company	Serial	VC/angel	On time	Backer success
Community share ($\times 10\text{pp}$)	0.070*** (0.009)	0.014*** (0.002)	0.017*** (0.002)	0.001 (0.002)	0.007*** (0.003)	0.016** (0.006)
Stranger share ($\times 10\text{pp}$)	0.087*** (0.010)	0.009*** (0.003)	0.019*** (0.002)	0.006*** (0.002)	0.002 (0.003)	0.003 (0.006)
Reference: family & friends						
Controls + FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7,282	8,234	8,211	4,492	6,876	4,185

Coefficients give the effect of shifting +10 percentage points of funding out of family/friends (the omitted reference) and into community or stranger funding, respectively. All models include the (log) amount pledged, (log) goal, (log) backers, a video indicator, a U.S. indicator, (log) updates and comments, and category and launch-year fixed effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.4 Scale contingency (H4): growth half holds, delivery half suggestive

H4 predicts that scale amplifies the asymmetric composition pattern: in larger campaigns, arm’s-length capital should look better on growth and (relative to embedded capital) worse on delivery. The data confirm the growth half clearly and the delivery half only suggestively.

Growth amplification (confirmed). The interaction between the standardized stranger share and the (log) goal on company formation is positive and significant ($b = +0.019$, $\text{SE} = 0.008$, $p = 0.016$; Table 6): in larger campaigns a higher stranger share is associated with substantially greater company formation. The parallel revenue interaction is positive and marginally significant ($b = +0.058$, $\text{SE} = 0.032$, $p = 0.07$). Figure 3 (left panel) plots the implied marginal effect of the stranger share on company formation across the goal range, which rises monotonically from a small effect in tiny campaigns to a sizeable, significant effect at the high end.

Delivery cost (suggestive). The companion on-time interaction has the predicted sign but does not reach conventional significance: $b = -0.015$ ($\text{SE} = 0.010$, $p = 0.12$ two-sided; one-sided $p \approx 0.06$). The implied marginal effect of the stranger share on on-time delivery descends from

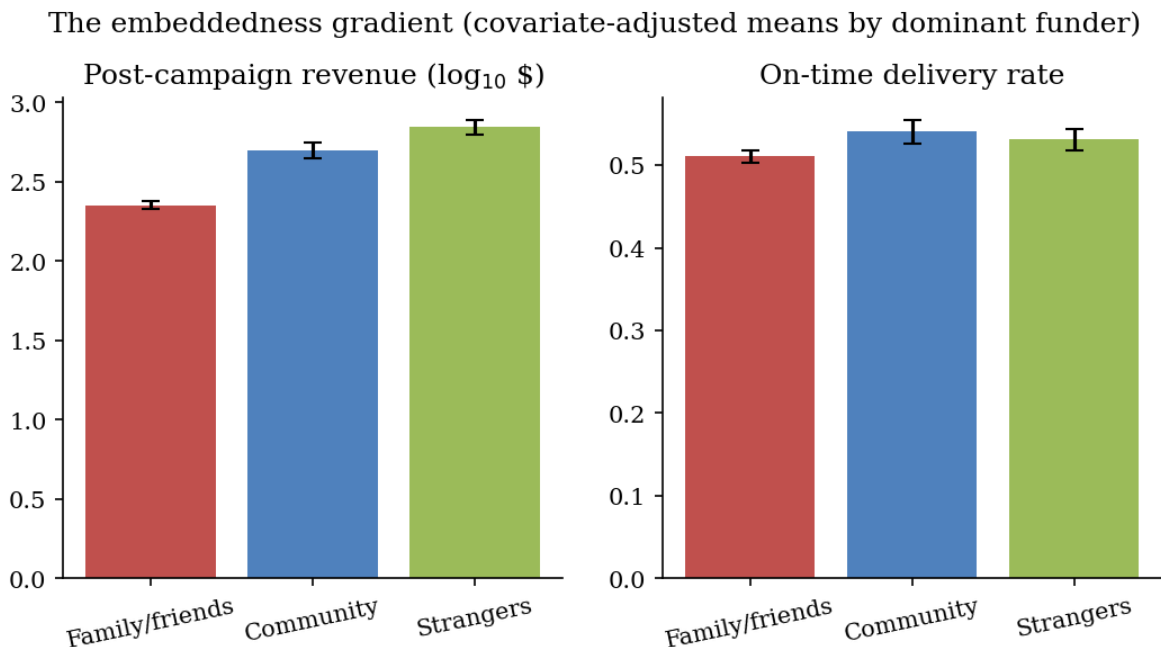


Figure 2: The embeddedness gradient. Covariate-adjusted means of (log) post-campaign revenue and on-time delivery by the funder type supplying the plurality of dollars. Family-dominated projects scale least; community-dominated projects scale like stranger-dominated projects but deliver more reliably.

+0.034 at a small goal (\$1,200) through approximately zero at the median goal (\$5,000) to -0.036 at a large goal (\$20,000), as shown in the right panel of Figure 3; the 95% band straddles zero throughout the range. The coarsened-exact-matching analysis in Section 6 recovers this same on-time gradient at marginal significance (ATT = -0.036 , $p = 0.06$), consistent with the predicted direction. We treat the growth half of H4 as supported and the delivery half as directionally consistent but statistically inconclusive.

5.5 Mechanisms

Among projects that experienced delivery delays, creators rated how much various factors contributed. A higher stranger share is associated with attributing delays *less* to stretch goals ($p < 0.01$), team and coordination problems ($p < 0.05$), and lack of money ($p < 0.10$), and not more to scope change (Table 7). Read alongside the gradient results, this is consistent with the interpretation that embedded—especially family-anchored—projects, when late, are delayed by under-resourcing and internal coordination frictions, whereas the delivery exposure of arm’s-length projects operates through the absence of relational monitoring in large undertakings rather than through scope creep. We treat these mechanism results as suggestive rather than dispositive.

Table 6: Moderation of the arm’s-length effect (interaction terms).

Outcome	Moderator M	Stranger $_z \times M$	N
Log revenue	Goal size	0.058* (0.032)	7,282
Log revenue	Product industry	-0.107** (0.046)	7,282
Log revenue	Female creator	0.021 (0.055)	4,840
Formed company	Goal size	0.019** (0.008)	8,234
Formed company	Product industry	-0.004 (0.012)	8,234
Formed company	Female creator	-0.027* (0.014)	5,451
On time	Goal size	-0.015 (0.010)	6,876
On time	Product industry	-0.012 (0.014)	6,876
On time	Female creator	-0.017 (0.017)	4,566

Each row is the stranger \times moderator interaction from a separate model; the stranger share is standardized. The negative on-time \times goal interaction (H4) is the key result. All models include the (log) amount pledged, (log) goal, (log) backers, a video indicator, a U.S. indicator, (log) updates and comments, and category and launch-year fixed effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Mechanisms: arm’s-length share and self-reported delay attributions.

Self-reported delay factor	Stranger $\times 10pp$	SE	N
Scope changed a lot (1–5, all projects)	–0.001	(0.007)	8,217
Delay: scope/direction changes (1–4)	–0.009	(0.007)	3,982
Delay: stretch goals (1–4)	–0.014***	(0.005)	3,900
Delay: team/coordination (1–4)	–0.012**	(0.006)	3,966
Delay: lack of money (1–4)	–0.011*	(0.006)	3,988
Delay: shipping/fulfillment (1–4)	0.005	(0.007)	3,985

Sample is projects reporting a delay (except row 1, all projects). Higher values mean the factor contributed more to the delay. All models include the (log) amount pledged, (log) goal, (log) backers, a video indicator, a U.S. indicator, (log) updates and comments, and category and launch-year fixed effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Robustness, Identification, and Limits

Estimator and sample sensitivity. Table 10 subjects the four headline outcomes to a battery of checks. Clustering standard errors by creator leaves inference unchanged. Adding demographic controls leaves the revenue and serial-founding effects essentially unchanged. Coarsened exact matching reproduces the scaling premium (revenue ATT = 0.34, $p < 0.001$; serial +0.038, $p < 0.05$) and recovers a marginal on-time penalty at high stranger shares (–0.036, $p < 0.10$). Entropy balancing yields the same revenue conclusion (0.26, $p < 0.001$). Re-estimating composition from the backer count rather than dollars is immaterial. The Oster coefficient-stability statistic is $\delta = 1.5$ for revenue and 3.7 for serial founding—selection on unobservables would need to be 1.5–3.7 times as strong as selection on the rich observables to explain away these results—while δ is small for company formation (0.58) and on-time delivery (0.04), consistent with our reading that those effects are fragile. Table 11 reports alternative estimators: Poisson (PPML) on revenue levels (Silva and

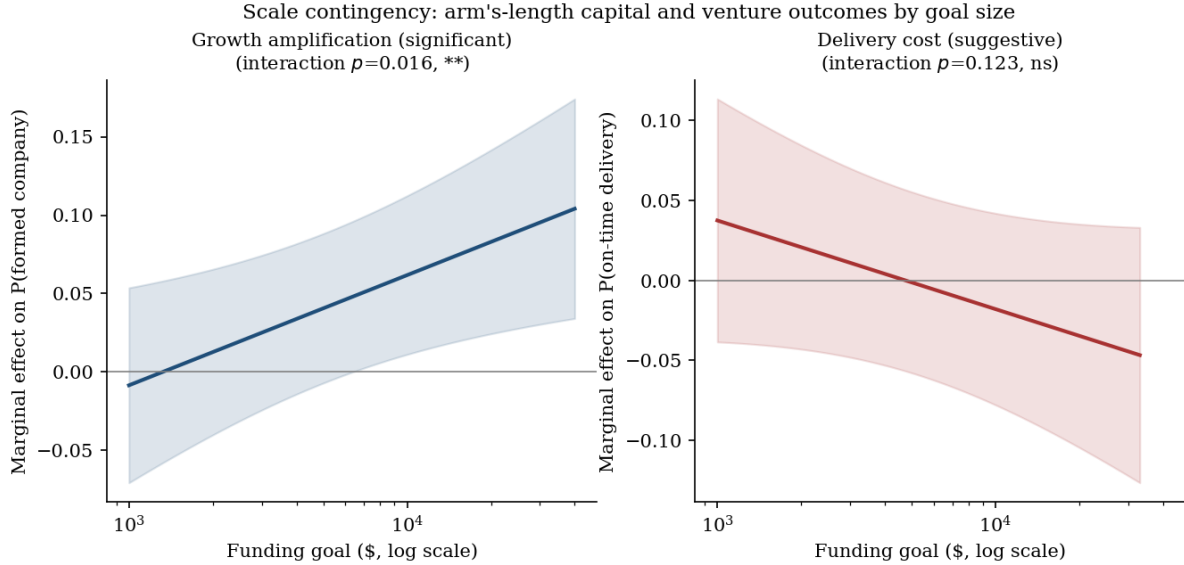


Figure 3: Scale contingency, both sides. Left: the marginal effect of the arm’s-length funding share on company formation rises significantly with goal size (interaction $p = 0.016$). Right: the analogous effect on on-time delivery descends from positive to negative, in the predicted direction, but the 95% band straddles zero throughout (interaction $p = 0.12$). Bands are 95% CIs; horizontal axis runs from the 5th to 95th percentile of (log) goal.

Tenreyro, 2006), ordered logit on the 12-category revenue scale, and average marginal effects from logit for the binary scaling outcomes. The logit AMEs (e.g., serial +0.013, VC/angel +0.005) are nearly identical to the LPM estimates and the ordered logit corroborates the revenue result ($p < 0.001$); the level-PPML coefficient is positive but imprecise.

Finer category controls, product vs. creative, and strict-coding sample. Table 8 pushes further on the most plausible threats. Replacing the 12 main categories with Kickstarter’s finer subcategories absorbs roughly 15% of the revenue coefficient (from 0.066 to 0.056) while leaving serial founding essentially unchanged; the on-time interaction sharpens slightly under subcategory fixed effects. Splitting the sample into product-oriented categories (Design, Food, Technology, Games, Fashion) and creative categories (everything else) yields a substantively important pattern: the revenue association is actually larger in creative categories ($b = 0.083$) than in product categories ($b = 0.046$), and VC/angel follow-on is significant only in the creative subsample. This complicates a simple “market validation flows to product-oriented ventures” story—if stranger demand were primarily valuable as a quality signal to downstream commercial investors, the effect should be largest where commercial scaling is most plausible. One reading is that within creative categories, stranger funding sharply discriminates the small subset of would-be commercial creative ventures from the majority; within product categories, stranger funding is more uniform and thus less discriminating. We treat this as suggestive rather than dispositive. Restricting to respondents whose three composition shares sum to 100 ± 5 ($N = 5,003$) leaves the revenue and serial associations

Table 8: Sensitivity to alternative samples and specifications.

Sample / specification	Log revenue	Serial	Formed company	On time
Baseline (full controls)	+0.0663*** (0.0094) $N = 7, 282$	+0.0139*** (0.0023) $N = 8, 211$	+0.0046* (0.0024) $N = 8, 234$	-0.0002 (0.0029) $N = 6, 876$
Pre-treatment controls only	+0.0658*** (0.0091) $N = 7, 282$	+0.0158*** (0.0022) $N = 8, 211$	+0.0025 (0.0024) $N = 8, 234$	-0.0053* (0.0028) $N = 6, 876$
Subcategory FE	+0.0580*** (0.0095) $N = 7, 282$	+0.0148*** (0.0024) $N = 8, 211$	+0.0045* (0.0025) $N = 8, 234$	-0.0001 (0.0029) $N = 6, 876$
Strict sample (sum= 100 \pm 5)	+0.0795*** (0.0126) $N = 4, 490$	+0.0147*** (0.0032) $N = 4, 985$	+0.0045 (0.0033) $N = 4, 996$	-0.0007 (0.0040) $N = 4, 148$
Product categories only	+0.0458*** (0.0139) $N = 1, 931$	+0.0118*** (0.0035) $N = 2, 195$	-0.0007 (0.0038) $N = 2, 202$	-0.0023 (0.0047) $N = 1, 901$
Creative categories only	+0.0827*** (0.0125) $N = 5, 351$	+0.0142*** (0.0028) $N = 6, 016$	+0.0070** (0.0031) $N = 6, 032$	+0.0030 (0.0036) $N = 4, 975$

Each cell is the stranger-share coefficient (per +10 percentage points) and clustered SE from a separate model. “Baseline” uses the full controls in Section 4. “Pre-treatment controls only” drops the (log) updates and (log) comments engagement controls, which are post-treatment relative to the campaign. “Subcategory FE” replaces the 12 main categories with Kickstarter’s finer subcategories. “Strict sample” restricts to respondents whose three composition shares sum to 100 \pm 5. “Product” and “Creative” partition projects by whether the category is product-oriented (Design, Food, Technology, Games, Fashion) or creative (everything else). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

intact (revenue $b = +0.080$, $p < 0.001$; serial $b = +0.015$, $p < 0.001$); company formation falls below conventional significance ($p = 0.17$) and on-time goes to zero in this stricter sample.

Outcome missingness. Several outcomes are observed on subsamples. Most outcome-missingness is unrelated to stranger share once we condition on the pre-treatment covariates (Table 9). Backer-rated success and backer satisfaction are the exceptions: their missingness is significantly associated with stranger share, but *in the opposite direction* from a simple embedded-response story. The coefficients on the missing indicators are negative ($b = -0.028$ and -0.028 per ten points, both $p < 0.001$), which means higher-stranger projects are *less* likely to be missing—they are *more* likely to be observed in the backer-survey outcomes. This is consistent with high-stranger campaigns having larger and more engaged backer bases that respond at higher rates when sampled. The backer-rated outcomes are therefore selected, but the selection runs against the direction one would worry about a priori (it is not that high-stranger projects are systematically underrepresented). Because backer-rated outcomes still rest on a non-random subset of projects, we treat them as less definitive than the larger-sample creator-side outcomes and note that on-time delivery (creator-reported, observed on a much larger subsample with no detectable missingness gradient) gives the cleaner read on the delivery question.

Outcome timing. The survey is administered after the campaign, and the question wording does not always cleanly partition pre- vs. post-campaign events. Two outcomes deserve particular caveats. “Company formation” is derived from the creator’s response about the legal vehicle used for the project; while many respondents formed an entity *for* the campaign, others used a pre-existing entity, and the dichotomization here cannot fully separate the two cases (a more conservative

Table 9: Outcome missingness and its association with the stranger share.

Outcome	Missing N / Total	% missing	Coef. on stranger×10pp
Revenue (post-campaign)	961 / 8,243	12%	−0.0018
VC/angel follow-on	3,751 / 8,243	46%	+0.0016
Has employees	2,583 / 8,243	31%	−0.0004
Backer-rated success	4,058 / 8,243	49%	−0.0279***
Backer satisfaction	4,286 / 8,243	52%	−0.0282***
On-time delivery	1,367 / 8,243	17%	−0.0011

Each row regresses a missing-indicator (1 if the outcome is unobserved) on the stranger share (per +10 percentage points), with the same pre-treatment controls and category and year fixed effects used in the main models. Backer-rated outcomes come from a parallel backer survey; their missingness is significantly associated with stranger share, which we discuss in the text. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

post-campaign-only “started a new related company” indicator is observed for a small subsample of creators and points in the same direction). “Press, award, or going viral” may have occurred during or after the campaign and could in principle have contributed to attracting stranger funding rather than resulted from it. “Serial founding” is unambiguously post-campaign. “Post-campaign revenue,” “VC or angel follow-on funding after the campaign,” and the delivery outcomes are by construction post-campaign. We retain the affected outcomes for transparency but the strongest scaling claim rests on revenue and serial founding, which are temporally clean and survive most checks.

Threats we cannot rule out. Three substantive confounders are not directly observed and could in principle explain the entire stranger–scaling association. (i) *Founder ambition or commercial intent*: founders who plan to build a firm may also work harder to attract strangers; if so, our coefficients reflect the consequences of ambition rather than the consequences of who funded the project. (ii) *Product-market fit and product quality*: projects that already have broad appeal will attract more strangers and grow more, with composition acting as a proxy. (iii) *Pre-existing audience and marketing capacity*: creators with more reach attract strangers and convert reach to later revenue. Matching, balancing, and Oster bounds discipline these threats relative to the observables we have but do not eliminate them. We therefore frame our estimates as conditional associations consistent with H1 and the H3 gradient, not as causal effects of composition.

7 Discussion

Across more than eight thousand funded Kickstarter projects, the social composition of crowd capital is associated with what a funded project becomes, over and above how much money it raised. The pattern is graded rather than dichotomous: family-and-friends capital is the growth laggard, community and stranger capital both outperform it on scaling, and community capital sits directionally above stranger capital on delivery and slightly below it on growth in a way

Table 10: Robustness of the arm’s-length effect across estimators and samples.

	Log revenue	Serial	Formed company	On time
Baseline (robust SE)	0.066*** (0.009)	0.014*** (0.002)	0.005* (0.002)	-0.000 (0.003)
Clustered by creator	0.066*** (0.009)	0.014*** (0.002)	0.005* (0.002)	-0.000 (0.003)
+ Demographics	0.064*** (0.011)	0.014*** (0.003)	0.006** (0.003)	-0.001 (0.004)
CEM (high vs low)	0.339*** (0.085)	0.038** (0.015)	-0.008 (0.021)	-0.036* (0.019)
Entropy balancing	0.263*** (0.080)	0.033 (0.025)	0.009 (0.025)	-0.012 (0.026)
Backer-count share	0.068*** (0.010)	0.013*** (0.002)	0.005* (0.002)	-0.002 (0.003)
Oster δ ($R_{max} = 1.3\tilde{R}$)	1.54	3.69	0.58	0.04

Cells report the stranger-share coefficient (per +10pp) and SE, except CEM/entropy-balancing rows, which report the average treatment effect on the treated of an above-median stranger share. Oster δ uses $R_{max} = 1.3\tilde{R}^2$; $|\delta| > 1$ implies robustness to selection on unobservables. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Alternative estimators for the arm’s-length effect.

Estimator	Outcome	Stranger effect	N
PPML (Poisson, levels)	Revenue (\$)	0.049 (0.041)	7,282
Ordered logit	Revenue (12 cat.)	0.076*** (0.009)	7,282
Logit (avg. marg. effect)	Formed company	0.0041* (0.0024)	8,234
Logit (avg. marg. effect)	VC/angel follow-on	0.0046** (0.0019)	4,492
Logit (avg. marg. effect)	Serial founding	0.0126*** (0.0020)	8,211

PPML is a Poisson model of revenue in levels; ordered logit uses the 12-category revenue scale; logit rows report average marginal effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

consistent with an embeddedness “sweet spot.” Direct equality tests show these community-vs-stranger differences are only marginally significant, so we read the gradient as a directional pattern within funded campaigns rather than as four statistically separable regimes.

What the design can and cannot say. Our estimates are conditional associations; whether composition *causes* the observed outcomes, or proxies for unobserved founder ambition, product-market fit, or audience size, is not pinned down by an observational design with retrospective self-reported composition. The most defensible substantive claim is that, among funded Kickstarter projects in the period studied, a higher arm’s-length share is a meaningful predictor of post-campaign revenue and serial founding even after rich controls, and that this association is robust across matching, balancing, alternative estimators, finer category controls, a strict-coding subsample, and a backer-count operationalization of composition. The associations for company formation, on-time delivery, and the scale-contingent delivery interaction are weaker and more fragile, and we treat them accordingly.

Theoretical contributions, restated narrowly. First, we offer a measurement contribution: the social composition of a funding base—family, community, and stranger shares—is a tractable,

project-level variable that complements the usual scalar of amount raised, and we show it has predictive content. Second, we extend embeddedness theory (Uzzi, 1997; Granovetter, 1973; Burt, 2004) from dyadic and network settings to the distributed setting of the crowd, and we show that Uzzi’s paradox is at least consistent with the empirical pattern: communities of weak embedded ties sit directionally between strangers and family-and-friends on growth and delivery. We do not claim the data adjudicate sharply between embeddedness and competing accounts based on founder ambition or product quality. Third, the descriptive pattern qualifies the democratization narrative in crowdfunding (Mollick, 2014; Agrawal et al., 2015; Sorenson et al., 2016): even within the funded sample, projects financed mainly by friends and family are the least likely to scale, suggesting that broad access to money does not by itself imply broad access to subsequent ventures.

Practical implications. For founders, the composition of one’s backers is a readable diagnostic. Reaching strangers is not merely a way to hit a funding goal; it is evidence of demand that predicts the venture’s future and that downstream investors appear to read. For platforms and policymakers hoping to broaden entrepreneurship through crowdfunding, the results counsel caution: helping under-networked founders raise money from their immediate circle may fund projects without enabling ventures. Tools that help founders convert intimate-tie support into community and, ultimately, market validation may matter more than funding success per se.

Limitations and future research. Our evidence is associational. The survey is retrospective and cross-sectional, composition is self-reported (though it exhibits strong internal and convergent validity), and the sample is restricted to funded projects, so survivorship and recall are concerns; reverse causality is possible if growth-oriented founders deliberately court strangers. Matching, entropy balancing, and coefficient-stability bounds constrain but do not eliminate selection on unobservables. Backer-side outcomes are observed for a subsample. Future work could exploit platform features that exogenously vary stranger exposure (editorial promotion, recommendation placement, or home bias (Lin and Viswanathan, 2016)), follow ventures longitudinally, and test whether the community sweet spot generalizes to equity crowdfunding (Vismara, 2016) and to serial founding dynamics (Butticè et al., 2017; Skirnevskiy et al., 2017).

8 Conclusion

Among funded Kickstarter projects, the social composition of the funding crowd—how much comes from family, from community, and from strangers—is associated with later venture outcomes after the amount raised, the goal, the number of backers, and category are accounted for. Within these conditional associations, family-and-friends capital is consistently the growth laggard, while community and stranger capital both outperform it, with community sitting directionally above stranger capital on delivery and slightly below it on growth in a way consistent with the embeddedness paradox. The design is not causal and several plausible unobservables remain, but the

descriptive pattern points to a research agenda: treating crowd capital as a socially composed object rather than a scalar, and asking under what conditions, for which categories, and for which founder types the relational character of money matters for what the money helps build.

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Appendix A. Summary statistics and correlations

Table 12: Summary statistics (analytic sample, $N = 8,243$).

Variable	N	Mean	SD	Median	Min	Max
Stranger (arm’s-length) share	8,243	0.247	0.276	0.110	0.000	1.000
Community share	8,243	0.242	0.225	0.196	0.000	1.000
Family & friends share	8,243	0.511	0.320	0.515	0.000	1.000
Post-campaign revenue (\log_{10})	7,282	2.520	1.837	2.700	0.000	7.000
Has employees	5,660	0.164	0.371	0.000	0.000	1.000
Formed a company	8,234	0.342	0.474	0.000	0.000	1.000
VC/angel follow-on	4,492	0.087	0.281	0.000	0.000	1.000
Launched another project	8,211	0.200	0.400	0.000	0.000	1.000
Press/award/viral	8,243	0.631	0.483	1.000	0.000	1.000
Delivered	8,226	0.851	0.357	1.000	0.000	1.000
Delivered on time	6,876	0.520	0.500	1.000	0.000	1.000
Backer-rated success (1–5)	4,185	4.157	0.850	4.000	1.000	5.000
Amount pledged (USD)	8,243	25,197	183,246	6,525	1,000	10,266,846
Goal (USD)	8,243	11,454	29,183	5,000	1.000	1,100,000
Backers	8,243	320.847	2,821	93.000	2.000	219,382
Female creator	5,456	0.407	0.491	0.000	0.000	1.000

Table 13: Pairwise correlations among composition, controls, and key outcomes.

	1	2	3	4	5	6	7	8	9	10	11	12
1 Stranger sh.	1.00	-0.20	-0.72	0.38	0.15	0.26	0.15	0.15	-0.10	-0.06	-0.21	0.45
2 Community sh.	-0.20	1.00	-0.53	0.09	0.10	0.09	0.07	0.06	0.02	0.06	-0.01	-0.07
3 Family sh.	-0.72	-0.53	1.00	-0.39	-0.19	-0.29	-0.18	-0.17	0.08	0.01	0.18	-0.34
4 Log pledged	0.38	0.09	-0.39	1.00	0.87	0.34	0.01	0.31	-0.18	-0.05	-0.09	0.34
5 Log goal	0.15	0.10	-0.19	0.87	1.00	0.24	-0.07	0.28	-0.16	-0.06	-0.01	0.20
6 Log revenue	0.26	0.09	-0.29	0.34	0.24	1.00	0.07	0.20	-0.06	0.09	-0.08	0.26
7 Serial	0.15	0.07	-0.18	0.01	-0.07	0.07	1.00	0.07	0.01	0.03	-0.10	0.04
8 Company	0.15	0.06	-0.17	0.31	0.28	0.20	0.07	1.00	-0.02	-0.03	-0.04	0.24
9 On time	-0.10	0.02	0.08	-0.18	-0.16	-0.06	0.01	-0.02	1.00	0.07	0.06	-0.08
10 Backer succ.	-0.06	0.06	0.01	-0.05	-0.06	0.09	0.03	-0.03	0.07	1.00	0.04	-0.09
11 Female	-0.21	-0.01	0.18	-0.09	-0.01	-0.08	-0.10	-0.04	0.06	0.04	1.00	-0.10
12 Product	0.45	-0.07	-0.34	0.34	0.20	0.26	0.04	0.24	-0.08	-0.09	-0.10	1.00