ONLINE APPENDIX

One of the known limitations of the VentureXpert dataset is the nonrandom disclosure of valuation data. Prior research has either ignored the issue (e.g., Shafi, Mohammadi, & Johan, 2019) or attempted to account for it using a Heckman selection model (Hochberg, Ljungqvist, & Lu, 2007; Hwang, Quingley, & Woodward, 2005). This method involves starting with an observable to calculate the likelihood that an investment round has available valuation data, then using the derived inverse Mills ratio in subsequent regression models (Heckman, 1979). We could not follow this method directly because the fixed effects of the conditional logit model would absorb the inverse Mills ratio. We still should be concerned, however, whether nonrandom selection has second-order effects. Specifically, even if we have controlled for the main effect of the inverse Mills ratio, it may still be possible that we have not accounted for its interaction with status asymmetry, which has the potential to affect our hypotheses.

To resolve this concern, we first followed the precedent in the finance literature (Hochberg, Ljungqvist, & Lu, 2010; Hwang et al., 2005) and constructed a model of the likelihood of valuation nondisclosure. We started by creating the investment round-level dataset of the 12,878 investment rounds that met all our preconditions (i.e., US portfolio companies that added a new US-based investor). We used year, industry, state, and investment stage fixed effects, as well as three additional variables that can reflect the prominence of the round and reduce the likelihood of nondisclosure: 1) the status of the lead VC investor; 2) the amount raised in the round; and 3) the market heat. Those variables can be thought of as instruments in the sense that they do not directly affect the dependent variable in our core equation; because they are round-level variables, they apply equally to both the factual and counterfactual observations, and the conditional logit completely absorbs their effects. Both, however, are correlated heavily with the likelihood of valuation nondisclosure. Table A1 presents our probit model, which predicts the availability of valuation trend data; Model 1 represents the main effects of our three main variables, whereas Models 2–4 progressively add the various fixed effects. We use Model 4 to construct the predicted probabilities and the inverse Mills ratios.

From that equation, we computed the likelihood of valuation disclosure and the associated inverse Mills ratio. While this ratio is defined at the round level—and thus cannot be used in our models based on round-level fixed effects—we can check whether incorporating its interactions with status asymmetry and market heat affects our core hypotheses. Table A2 presents those interactions. Models 1–4 focus on the conditional logit specification. Model 1 is the baseline model testing H1 and H2 (as in Table 3, Model 5, in the main paper). Model 2 adds the interactions between the inverse Mills ratio and the upward- and downward-status asymmetries, finding that the main coefficients of interest have not changed materially. Similarly, Model 3 represents our reference model testing H3 (as in Table 4, Model 8, in the main paper). Model 4 shows that the three-way interaction between upward-status asymmetry, performance trend, and market heat is robust to including the three-way interaction between status asymmetry, performance trend, and the inverse Mills ratio. Models 5–8 repeat the same set of analyses using the fixed effects linear probability models based on specifications from Table 4 in the main paper. The fact that the interactions of interest are affected only slightly when introducing parallel interactions involving the inverse Mills ratio is reassuring for the stability of our results and reduces concerns that selective disclosure may be affecting our results.

References:

Heckman, J. J. 1979. Sample selection bias as a specification error. ***Econometrica***, 47(1): 153-161.

Hochberg, Y. V., Ljungqvist, A., & Lu, Y. 2007. Whom you know matters: Venture capital networks and investment performance. ***Journal of Finance***, 62(1): 251-301.

Hochberg, Y. V., Ljungqvist, A., & Lu, Y. 2010. Networking as a barrier to entry and the competitive supply of venture capital. ***Journal of Finance***, 65(3): 829-859.

Hwang, M., Quingley, J., & Woodward, S. 2005. An index for venture capital, 1987–2003. ***Contributions to Economic Analysis and Policy***, 4(1): 1-43.

Shafi, K., Mohammadi, A., & Johan, S. 2019. Investment ties gone awry. ***Academy of Management Journal***, forthcoming.

TABLE A1
Probit models predicting the availability of valuation trend data

	Model 1	Model 2	Model 3	Model 4
Constant	-1.010***	-0.866***	0.0264	-1.261***
	(-42.93)	(-18.64)	(0.09)	(-3.45)
Status of the Lead	0.300***	0.240***	0.263***	0.621***
	(5.58)	(4.37)	(4.64)	(8.86)
Round size (logged)	0.00373***	0.00368***	0.00365***	0.00651***
	(7.17)	(6.95)	(6.84)	(10.34)
Market heat	0.684***	0.822***	0.817***	0.160**
	(26.17)	(28.74)	(28.32)	(3.21)
Industry fixed effects	NO	YES	YES	YES
State fixed effects	NO	NO	YES	YES
Year fixed effects	NO	NO	NO	YES
Pseudo R-square	0.0596	0.0871	0.0998	0.3291
Log Likelihood	-6644	-6436	-6349	-4707
Observations	12878	12878	12878	12878

Note: T-statistics in parentheses.
*p < .05
**p < .01
***p < .001

TABLE A2

Conditional logit and fixed effect linear probability models predicting factual ties, with fixed effects based on groups of one factual observation and the associated counterfactual observations

	Conditional logit				Fixed effect linear probability model			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
Constant					0.130***	0.130***	0.130***	0.131***
					(5.33)	(5.33)	(5.29)	(5.30)
Follower IPO percentage	0.540***	0.534***	0.531***	0.528***	0.0697***	0.0689***	0.0685***	0.0681***
	(5.43)	(5.37)	(5.33)	(5.29)	(4.96)	(4.90)	(4.88)	(4.85)
Follower investment count	-0.313***	-0.313***	-0.309***	-0.309***	-0.0353***	-0.0352***	-0.0349***	-0.0349***
	(-9.60)	(-9.58)	(-9.44)	(-9.44)	(-9.83)	(-9.81)	(-9.67)	(-9.67)
Follower fund count	-0.233***	-0.234***	-0.235***	-0.235***	-0.0225***	-0.0226***	-0.0226***	-0.0226***
	(-6.41)	(-6.43)	(-6.45)	(-6.45)	(-6.09)	(-6.12)	(-6.11)	(-6.12)
Follower age	-0.130***	-0.131***	-0.134***	-0.134***	-0.0160***	-0.0161***	-0.0164***	-0.0164***
	(-5.62)	(-5.64)	(-5.74)	(-5.76)	(-5.92)	(-5.95)	(-6.05)	(-6.07)
Follower industry specialization	-0.505***	-0.509***	-0.508***	-0.510***	-0.0630***	-0.0636***	-0.0634***	-0.0638***
	(-5.43)	(-5.47)	(-5.45)	(-5.47)	(-5.88)	(-5.94)	(-5.91)	(-5.95)
Follower state specialization	-0.845***	-0.846***	-0.855***	-0.857***	-0.0936***	-0.0936***	-0.0941***	-0.0942***
	(-8.84)	(-8.85)	(-8.94)	(-8.95)	(-9.23)	(-9.23)	(-9.28)	(-9.28)
Follower distance to company	-0.0534***	-0.0534***	-0.0539***	-0.0538***	-0.00580***	-0.00579***	-0.00582***	-0.00581***
	(-5.15)	(-5.15)	(-5.19)	(-5.19)	(-5.17)	(-5.17)	(-5.20)	(-5.19)
Industry overlap between lead and follower	-0.122	-0.126	-0.132	-0.137	-0.0234*	-0.0238*	-0.0246*	-0.0250*
	(-1.15)	(-1.19)	(-1.25)	(-1.29)	(-2.03)	(-2.06)	(-2.13)	(-2.17)
State overlap between lead and follower	0.544***	0.548***	0.546***	0.551***	0.0555***	0.0558***	0.0559***	0.0562***
	(4.67)	(4.70)	(4.69)	(4.72)	(4.48)	(4.50)	(4.51)	(4.53)
Distance between lead and follower	-0.0178*	-0.0178*	-0.0179*	-0.0181*	-0.00180*	-0.00181*	-0.00182*	-0.00183*
	(-2.17)	(-2.17)	(-2.19)	(-2.21)	(-2.02)	(-2.02)	(-2.04)	(-2.05)
Direct ties between lead and follower	0.590***	0.589***	0.592***	0.592***	0.0640***	0.0640***	0.0644***	0.0643***
	(16.53)	(16.53)	(16.62)	(16.60)	(16.23)	(16.23)	(16.33)	(16.33)
Indirect ties between lead and follower	0.429***	0.430***	0.431***	0.432***	0.0528***	0.0528***	0.0529***	0.0529***
	(9.51)	(9.50)	(9.52)	(9.50)	(11.24)	(11.25)	(11.22)	(11.23)
Assortative matching (superior follower)	-0.626*	-0.606*	-0.651*	-0.631*	-0.0374	-0.0348	-0.0400	-0.0370
	(-2.27)	(-2.19)	(-2.34)	(-2.25)	(-1.37)	(-1.28)	(-1.45)	(-1.33)
Assortative matching (superior company)	0.436*	0.441*	0.468**	0.474**	0.0222	0.0224	0.0246	0.0246
	(2.43)	(2.45)	(2.59)	(2.61)	(1.07)	(1.08)	(1.18)	(1.17)
Upward-status asymmetry (A)	-0.474**	-1.291	-0.488**	-0.896	-0.0772***	-0.174*	-0.0846***	-0.137
	(-2.63)	(-1.84)	(-2.69)	(-1.22)	(-3.76)	(-2.28)	(-4.01)	(-1.63)
Downward-status asymmetry (B)	1.145***	1.306**	1.192***	1.282**	0.166***	0.195***	0.172***	0.190***
	(7.40)	(3.24)	(7.63)	(2.98)	(8.88)	(4.14)	(9.13)	(3.67)
A × Valuation trend	0.754***	0.756***	0.401*	0.409*	0.0743***	0.0745***	0.0366*	0.0376*
	(5.08)	(5.10)	(2.28)	(2.32)	(5.52)	(5.54)	(2.19)	(2.24)
B × Valuation trend	-0.282***	-0.286***	-0.223**	-0.226**	-0.0358***	-0.0364***	-0.0287***	-0.0294***
	(-4.14)	(-4.17)	(-2.81)	(-2.82)	(-4.88)	(-4.92)	(-3.30)	(-3.32)
A × IMR		1.526		0.737		0.180		0.0946
		(1.19)		(0.54)		(1.29)		(0.61)
B × IMR		-0.312		-0.182		-0.0567		-0.0350
		(-0.45)		(-0.24)		(-0.71)		(-0.38)
A × Market heat			-0.170	-2.067			-0.0107	-0.172
			(-0.70)	(-1.37)			(-0.47)	(-1.18)
B × Market heat			-0.135	-0.202			-0.0114	-0.00162
			(-1.09)	(-0.23)			(-0.84)	(-0.02)
A × Market heat × Valuation trend			0.678**	0.719**			0.0722***	0.0766***
			(3.01)	(3.29)			(3.74)	(3.97)
B × Market heat × Valuation trend			-0.0905	-0.0860			-0.0136	-0.0131
			(-0.94)	(-0.87)			(-1.37)	(-1.27)
A × Market heat × IMR				3.391				0.286
				(1.25)				(1.09)
B × Market heat × IMR				0.116				-0.0183
				(0.07)				(-0.10)
Observations	45377	45377	45377	45377	45377	45377	45377	45377
Pseudo R-squared	0.064	0.0641	0.065	0.0652	0.0359	0.036	0.0366	0.0367

Note: Incorporates inverse Mills ratio (IMR) from the first-stage equation on Table A1, Model 4. Robust standard errors clustered around factual-counterfactual groups; t-statistics in parentheses.

*$p < .05$

**$p < .01$

***$p < .001$