

## DOES SOCIAL PROXIMITY ENHANCE BUSINESS RELATIONSHIPS?<sup>1</sup>

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### Introduction

In 2004, Vinod Khosla, Indian billionaire and co-founder of Sun Microsystems, started Khosla Ventures. By 2011, the Silicon Valley-based venture capital firm's portfolio included US companies founded or co-founded by: Ramesh Chandra (MokaFive), Sriniv Devadas (Verayo), Yogi Goswami (Sunborne), Sandeep Gulati (Zyomed), Siraj Khaliq (WeatherBill), Ramu Krishnan (Ramu Inc.), Ashok Krishnamurthi (Xsigo), Hosain Rahman (Aliph), Anil Rao (Sea Micro), Mulpuri Rao (Soladigm), Bindu Reddy (MyLikes), Mohit Singh (Seeo), and Adya Tripathi (Tula). If we added CEOs' and Directors' names, the list of executives of Indian origin in Khosla's portfolio of companies would grow longer still. Khosla Ventures does not advertise a preference for investing in companies started by ethnic Indians, but casual observation suggests that it has one. Is this a costly indulgence of discriminatory preferences, a clever business strategy taking advantage of superior social capital, neither, or both? In this paper we examine how social proximity affects both the choice of business partners as well as subsequent performance.

We investigate the interaction of two conceptually distinct mechanisms that shape the performance of socially proximate business partnerships: *selection* and *influence*. Individuals may have better access to, and superior information about, opportunities within their social

networks. Furthermore, individuals with common experience and communication styles may be able to interpret signals of quality more precisely. Social proximity may thus facilitate business partner *selection*. After forming a partnership, shared norms and discourse may improve coordination and monitoring among socially close individuals – hence, proximity may positively *influence* the partnership *after* formation.

In prior work (Hegde and Tumlinson 2014) we formalize these mechanisms in a game theoretic model, in which the actors are only motivated by financial rewards (rather than, say, discriminatory preferences), and generate the following propositions about the circumstances under which socially proximate agents are likely to partner and succeed:

1. Socially proximate partnerships will be of lower observable quality at formation.<sup>4</sup>
2. Socially proximate partnerships are more likely to succeed.<sup>5</sup>
3. Socially proximate individuals are more likely to partner.

A casual observer might perceive the first prediction as taste-based discrimination, but it is not – those choosing partners set the same minimum success probability for all candidates. There are two reasons that the quality signal denoting this minimum probability is lower for socially proximate candidates: First, when a close candidate sends a “high” quality signal, it indicates high quality with greater certainty than when a distant candidate does so. Second, the chooser knows he can compensate for low quality, to some extent, with positive influence *after* partnering. Hence, one has generally observed quality signals from his socially close partners that are lower.

We test our model's predictions over the social proximity induced by shared ethnicity in the context of the business partnerships formed between venture capital firm (VC) partners (VC “partners” are principals who make, and monitor, investments) and startup executives

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<sup>4</sup> This result assumes that absent any specific signal of a potential partner's quality he would be rejected.

<sup>5</sup> Our proof utilizes normally distributed errors in the quality signals.

Table 1

Ethnic proximity and probability of VC-company match			
Ethnic group	Actual VC-Company pairs	Counterfactual pairs	Difference
COETHNIC ANGLO-CELTIC	0.912	0.857	0.055
COETHNIC WEST EUROPEAN	0.566	0.463	0.103
COETHNIC SOUTH EUROPEAN	0.235	0.149	0.086
COETHNIC EAST EUROPEAN	0.114	0.077	0.037
COETHNIC NORTH EUROPEAN	0.103	0.061	0.042
COETHNIC INDIAN	0.098	0.040	0.058
COETHNIC JEWISH	0.091	0.052	0.039
COETHNIC CHINESE	0.041	0.016	0.024
COETHNIC KOREAN	0.007	0.003	0.003
COETHNIC JAPANESE	0.004	0.002	0.002
COETHNIC OTHER	0.114	0.067	0.047
COETHNIC DISTINCT GROUPS <sup>a)</sup>	0.466	0.311	0.155
COETHNIC INDISTINCT GROUPS <sup>b)</sup>	0.955	0.914	0.041
COETHNIC ALL GROUPS	0.970	0.935	0.035
MAHALANOBIS ETHNIC DISTANCE	10.35	14.15	-3.79

<sup>a)</sup> For both actual and counterfactual pairs, “COETHNIC DISTINCT GROUPS” = 1 if any of (COETHNIC SOUTH EUROPEAN, COETHNIC EAST EUROPEAN, COETHNIC NORTH EUROPEAN, COETHNIC INDIAN, COETHNIC JEWISH, COETHNIC CHINESE, COETHNIC KOREAN, COETHNIC JAPANESE) = 1

<sup>b)</sup> For both actual and counterfactual pairs, “COETHNIC INDISTINCT GROUPS” = 1 if any of (COETHNIC ANGLO-CELTIC, COETHNIC WEST EUROPEAN, COETHNIC OTHER) = 1

Notes: The table compares sample means for the different measures of coethnicity for actual VC-company pairs (Column 1), counterfactual VC-company pairs (Column 2), and the difference between the two (Column 3). All differences are statistically significant at 95% confidence levels.

Source: Hegde and Tumlinson (2014).

using a sample of almost all US venture-backed deals between 1991 and 2010. We assemble the names of 22,000 US-based VC partners and 85,000 US-based startup executives from the rosters of 2,687 VCs and 11,235 startups that they funded and classify each partner and executive, based on their family name (surname) and given name, as belonging to one of ten distinct ethnic groups. Then, for each investment, we compute a binary measure of coethnicity between the investing VC and funded startup indicating whether the VC and the company have top-level personnel of the same ethnicity (e.g. COETHNIC-INDIAN or COETHNIC-CHINESE). We also calculate a continuous measure of ethnic distance between each VC-company pair (i.e. ETHNIC DISTANCE). One may wonder from our example above whether Khosla Venture’s investments reflect the preferences of Indian venture capitalists and entrepreneurs for the IT sector or Silicon Valley, rather than ethnic proximity among individuals of the Indian community. To control for these factors, we gather information on investment, VC, and company characteristics, including investment amount, geographic distance between VC and company (i.e. GEOGRAPHIC DISTANCE), as well

as similarity in VC and company industry specialization (i.e. INDUSTRY DISTANCE).<sup>6</sup>

### Does ethnic proximity affect VC-company matching?

#### Proximity and matching

We first show that Khosla Ventures’ investment strategy is not unique. To this end, we construct a sample of VC-company pairs, both actual, for which the investment happened, and counterfactual, for which investment could have happened (i.e. the VCs and companies were operating in the same industry at the same time), but did not.

Table 1 reveals that coethnic personnel are, on average, more likely for actual VC-company pairs than counterfactual pairs: the difference in matching likelihood

<sup>6</sup> Lerner (1995), Sorenson and Stuart (2001), Agrawal (2008) and Kerr (2008) have all discussed the role geographic proximity/clustering in VC investment and performance.

Table 2

Relationship between ethnic proximity and probability of VC-company match			
D.V. = VC-Company match (0/1)	1	2	3
COETHNIC ANGLO-CELTIC	0		
COETHNIC CHINESE	0.0008**		
COETHNIC EAST EUROPEAN	0.0002		
COETHNIC INDIAN	0.0009**		
COETHNIC JAPANESE	0.0004		
COETHNIC JEWISH	0.0004*		
COETHNIC KOREAN	0.0002		
COETHNIC NORTH EUROPEAN	0.0003+		
COETHNIC SOUTH EUROPEAN	0.0004**		
COETHNIC WEST EUROPEAN	0.0001		
COETHNIC OTHER	0.0001		
COETHNIC DISTINCT GROUPS		0.0004**	
COETHNIC INDISTINCT GROUPS		0.0001	
LOG ETHNIC DISTANCE			-0.0004**
LOG GEOGRAPHIC DISTANCE	-0.0006**	-0.0006**	-0.0006**
INDUSTRY DISTANCE	-0.0025**	-0.0025**	-0.0025**
LOG N. OF CO EXECUTIVES	0.0004**	0.0005**	0.0004**
LOG N. OF VC PARTNERS	0.0006**	0.0007**	0.0006**

Notes: The table displays marginal effects derived from Probit estimates of the relationship between ethnic distance and the probability that a VC invested in the startup company with which it is paired. A VC-company pair is the unit of analysis in the regressions. The dependent variable is set to one for actual VC-company pairs (i.e. pairs for which the VC invested in the company) and zero for counterfactual VC-company pairs. All regressions, in all remaining tables include Company-Year, VC-Year and Industry fixed effects. We use \*\*, \*, and + to denote  $p < 0.01$ ,  $p < 0.05$  and  $p < 0.1$  respectively, computed from robust standard errors clustered at the VC level, in all remaining tables (except columns 3 and 4 of Table 4 where robust standard errors are clustered by state-industry-funding year).

Source: Hegde and Tumlinson (2014).

is statistically significant (at  $p < 0.05$ ) for all ten ethnic groups. Next, we formally investigate the relationship between ethnic proximity and the probability of VC-company match with multivariate Probit regressions. Table 2 reports the marginal effects of the influence of the explanatory variables on the probability of a VC-company match.

Column 1 confirms that after controlling for geographic distance, industry distance, founding-year effects of VCs and companies, the proportion of different ethnic individuals in VCs and companies and industry-specific effects, coethnicity is positively related to the probability of a VC-company match for all ethnic groups (except for individuals of Anglo-Celtic origin). The positive effect of coethnicity is statistically significant (at  $p < 0.05$ ) for Chinese, Indian, Jewish, and South European ethnicities (the South European group is more homogenous than other European groups and is composed primarily of individuals with origins in Italy and Spain).

Column 2 shows that the *average* marginal effect of a single coethnic pair on matching for members of distinct ethnic groups (Chinese, Indian, Japanese, Jewish, Korean, East European, North European and South European) is nearly four times coethnicity's effect for

the "indistinct" groups (Anglo-Celtic, West European and Others); in fact, coethnicity's estimated effect for the latter does not statistically differ from zero. The magnitude of the marginal effects may appear small (a single coethnic pair increases the probability that a VC invests in the given company by 0.04 percentage points), but the unconditional probability of a VC-company pair match in our sample is 0.25 percent, implying that an additional coethnic pair is associated with a 16 percent higher probability of a match – an economically substantial effect. Column 3 confirms the positive effect of ethnic proximity using our measure of ethnic distance.

#### *Proximity, matching and quality signals*

According to our first theoretical prediction, VCs screen coethnic investments less stringently, both because VCs are surer that the coethnic company they are evaluating is of the indicated quality and because they know that coethnicity's positive influence effects will compensate for lower quality at the time of investment. Although we cannot measure the quality signals observed by the VCs when it invested, we can check whether VCs are more likely to invest in coethnic startups associated with lower quality signals by using information *ex ante* generally correlated with the startup success.

Table 3

## Relationship between ethnic proximity and probability of VC-company match by funding round and company life-stage

Panel A					
Funding Round	1	2	3	4	
COETHNIC DISTINCT GROUPS	0.0003**	0.0001**	0.0001*	0.0001	
LOG GEOGRAPHIC DISTANCE	-0.0004**	-0.0002**	-0.0002**	-0.0001**	
INDUSTRY DISTANCE	-0.0026**	-0.0013**	-0.0010**	-0.0009**	
LOG N. OF CO EXECUTIVES	0.0001*	0.0001**	0.0002**	0.0002**	
LOG N. OF VC PARTNERS	0.0004**	0.0002**	0.0002**	0.0002**	
Panel B					
Life-cycle Stage	Seed	Early	Expansion	Late	Acquisition
COETHNIC DISTINCT GROUPS	0.0003**	0.0003**	0.0003**	0.0002	0.0001
LOG GEOGRAPHIC DISTANCE	-0.0003**	-0.0004**	-0.0004**	-0.0003**	-0.0003**
INDUSTRY DISTANCE	-0.0023**	-0.0025**	-0.0026**	-0.0019**	-0.0029**
LOG N. OF CO EXECUTIVES	0.0001	0.0001	0.0001	0.0002+	0
LOG N. OF VC PARTNERS	0.0003**	0.0004**	0.0003**	0.0003**	0.0006**

Notes: Panel A displays marginal effects derived from Probit estimates of the relationship between ethnic distance and the probability that a VC invested in the startup company with which it is paired separately for the first four rounds of funding. Panel B marginal effects derived from Probit estimates of the relationship between coethnicity and the probability that a VC invested in the startup company with which it is paired for companies at different life stages during the VCs first round of funding for the company. A VC-company pair is the unit of analysis in the regressions. The dependent variable is set to one for actual VC-company pairs (i.e. pairs for which the VC invested in the company) and zero for counterfactual VC-company pairs.

Source: Hegde and Tumlinson (2014).

Rather than providing all the capital required by startups upfront, VCs inject capital into their portfolio companies in successive stages or “rounds.” This staged infusion allows VCs to learn about the quality and prospects of startups, while preserving their option to discontinue funding if the venture appears unlikely to succeed (e.g. Bergemann and Hege 1998, Wang and Zhou 2004). Hence, the average success probability of startups at first-round funding ( $R1$ ) is lower than the success probability of startups that receive second-round funding ( $R2$ ), which is lower than the success probability of startups that survive into the third round ( $R3$ ), and so on.<sup>7</sup> If VCs are more likely to select coethnic ventures in earlier rounds, then this will provide evidence that VCs tolerate lower quality signals from coethnic startups.

Panel A of Table 3 suggests that ethnic proximity plays a more significant role in matching VCs to companies during earlier rounds, when VCs face the highest search and screening costs. An additional coethnic pair is associated with an increase in the probability of matching by 0.03 percent in the first round (both at  $p < 0.01$ ); for the second and third rounds, the effect drops to 0.01 percent ( $p < 0.05$ ) and does not statistically differ from zero for the fourth round. Although we do not report the estimates for later rounds, we find that the es-

timated effect of coethnicity for rounds  $R5$  and higher were not statistically different from zero. Interestingly, the estimated effects of geographic and industry proximity also follow a similar pattern, consistent with the explanation that search and selection advantages conferred by collocation and cospecialization become less salient as noise about companies’ quality decreases.

The probability of startups’ success also depends on their life-stage. As a startup matures, ideas become tangible products, business plans translate into verifiable costs and revenues, expansion plans can be better evaluated, and the probability of subsequent failure diminishes. Thus, an alternative test for our first theoretical prediction is that coethnic VCs should be more likely to invest in less mature (i.e. lower *ex ante* quality) companies. Since the progress of startups along their life-cycle correlates highly with the number of investment rounds received, we limit attention to the first time the startups receive venture funding – do coethnic VCs invest in less mature companies in  $R1$ ? Of the 10,134 startups in our  $R1$  sample, 21 percent were denoted as “Seed Stage,” 41.7 percent as “Early Stage,” 16.4 percent as “Expansion Stage,” 3.7 percent as “Late Stage,” and 17.3 percent as “Buyout and Acquisition Stage.” The estimates in Panel B of Table 3 confirm that ethnic proximity most significantly predicts VC-startup matching during the first round of investment for Seed Stage, Early Stage, and Expansion Stage companies (es-

<sup>7</sup> In our sample, firms that received funding in  $R1$ ,  $R2$ ,  $R3$  and  $R4$  had IPO probabilities of 7.7 percent, 9.4 percent, 11.1 percent, and 12.2 percent respectively.

Table 4

Relationship between ethnic proximity and probability of successful exit					
	1	2	3	4	5
D.V. = IPO+Acquired (0/1)	$dy/dx$	OLS	2SLS	2SLS	Heckman
COETHNIC DISTINCT GROUPS	0.031**	0.025*	0.121**	0.169**	0.133**
LOG GEOGRAPHIC DISTANCE	-0.002	-0.004*	-0.004*	-0.003+	-0.178**
INDUSTRY DISTANCE	-0.122**	-0.070*	-0.071*	-0.068*	-0.810**
LOG N. OF CO EXECUTIVES	0.205**	0.163**	0.142**	0.131**	0.241**
LOG TOTAL FUNDING	0.018**	0.029**	0.029**	0.029**	0.014**
LOG N. OF VC PARTNERS	0.045**				0.210**
Inverse Mills Ratio					1.618**

Notes: The table displays estimates of the relationship between ethnic proximity and the probability that the company exits through acquisitions and IPOs. The estimation sample consists of actual VC-company pairs, formed across different rounds of funding and the dependent variable is set to one if the company exited through an IPO or acquisition, and zero otherwise. Column 1 presents marginal effects derived from Probit estimates. Column 2 presents baseline OLS estimates. Column 3 displays 2-Stage Least Squares (2SLS) estimates obtained by using the average of the binary measure of “COETHNIC DISTINCT GROUPS” for each focal company’s state-industry-funding year as an instrument for COETHNIC DISTINCT GROUPS. Column 4 displays 2-Stage Least Squares (2SLS) estimates obtained by using fixed effects for the states, industries, and years, as well as fixed effects for the interactions of state-industry and industry-funding years as instruments for COETHNIC DISTINCT GROUPS. Column 5 presents the second-stage of the Heckman selection-correction model. The first stage is estimated with the full set of explanatory variables and the instrument used for the estimations in Column 3 to satisfy the exclusion restriction.

Source: Hegde and Tumlinson (2014).

estimated effect of 0.03 percent at  $p < 0.01$  in each case), and has no statistically significant effect for either Late Stage or Buyout and Acquisition Stage, when the probability of company failure is relatively low.<sup>8</sup>

Finally, the distribution of company age at the time of initial venture investment also indicates that VCs accept lower quality signals from ethnically closer companies. The average startup company that closes its first funding round with a non-coethnic VC (as before, “coethnic” denotes shared ethnicity among individuals belonging to one of the eight distinct groups) does so 985 days after incorporation compared to 901 days (nearly a full quarter-of-a-year later) for one funded by a coethnic VC. Hence, coethnic investments appear to be associated with lower quality signals, as suggested by our theory.

### Is proximity related to superior performance?

#### *Successful exits through IPOs and acquisitions*

Performance also differs with ethnic proximity. Table 4 presents Probit estimates of the relationship between proximity and successful exits measured by a binary

dependent variable equal to one if the company went public or was acquired, and zero for all other outcomes. Column 1 shows that shared ethnicity is positively associated with the probability of successful exit for distinct ethnic groups. Switching the ethnicity of one VC partner to that of a company executive increases the probability of successful exit by 3.1 percent.

Next, we control for the unobserved quality of VC partners by incorporating VC-fixed effects (which control not only for VC-quality, but also other unobserved VC characteristics, which may influence their investment performance, such as access to syndicates of co-investors, managerial talent pools, reputation, stage preferences and access to capital). Rather than Probit, we estimate VC-fixed effects regressions as Linear Probability Models. Column 2 of Table 4 shows that in the model with VC-fixed effects, the estimated average effect of a coethnic pair (for distinct ethnic groups) on the probability of successful exit (2.5 percent) is comparable to the estimated marginal effect of coethnicity without (3.1 percent). Thus, even *within* a given VC’s portfolio, startup companies that are ethnically closest to the VCs perform best.

<sup>8</sup> In our sample of firms that received R1 funding, those in the Buyout and Acquisition phase had an IPO probability of 13 percent, while firms in the earlier stages had IPO probabilities in the 5.7–8.3 percent range.

Table 5

Relationship between ethnic proximity and post-IPO performance				
	Market capitalization (million USD)		Net income (million USD)	
COETHNIC DISTINCT GROUPS	0.091*	0.111*	0.005*	0.009+
LOG GEOGRAPHIC DISTANCE	-0.012+	-0.011	-0.272	-0.897
INDUSTRY DISTANCE	-0.302**	-0.370+	9.174	0.658
LOG N. OF CO EXECUTIVES	0.350**	0.311**	2.262	0.204
LOG TOTAL FUNDING	0.113**	0.147**	-1.758*	-2.498+
LOG N. OF VC PARTNERS	0.036+		2.201+	
VC Fixed effects	N	Y	N	Y

The table displays Ordinary Least Squares estimates of the relationship between ethnic proximity and post-IPO performance. The estimation sample consists of 2,943 actual VC-company pairs for companies with data on market capitalization and 1,316 actual VC-company pairs for companies with data on net income one year after IPO.

Source: Hegde and Tumlinson (2014).

### Isolating ethnic proximity's influence effects

These results are based on correlations obtained after controlling for the observable characteristics of VCs and companies, but do not distinguish between the effects of ethnicity-based *selection* of high-quality investments and coethnicity's *influence* on performance through enhanced coordination between investors and entrepreneurs. We try to isolate the influence effects ("treatment effect" in econometric parlance) of coethnicity by employing three separate econometric strategies: (a) an instrumental variables (IV) approach that accounts for omitted variables, such as unobserved VC and company quality, that affect performance through selection; (b) a method developed by Akerberg and Botticini (2002), also based on IVs, that isolates the effect of exogenous market characteristics unrelated to the influence effects of coethnicity on performance; and (c) a two-stage Heckman (1979) model that corrects for a broader set of factors that affect selection (including unobserved quality) while predicting performance. The technicalities of these analyses are detailed in Hegde and Tumlinson (2014); however, as shown respectively in Columns 3, 4 and 5 of Table 4, all yield estimates of coethnic influence substantially larger than OLS estimates and suggest that coethnicity improves performance through strong post-investment *influence*.

Our finding that ethnic proximity facilitates VC-company matching, particularly during early funding rounds, when the probability of the startups' success is low, taken together with our two-stage estimates, implies that VCs select coethnic companies (over

non-coethnic ones) even when they appear to be of *lower* observable quality. While counterintuitive, such behavior aligns with theoretical predictions based on our model of shared discourse systems between coethnic partners. The model suggests that because VCs read the signals from coethnic companies more *precisely*, and because VCs *anticipate* coethnicity's positive post-investment influence, lower quality signals from coethnic companies suffice to trigger investment.

Moreover, the strong positive post-investment effects of coethnicity persist even after successful exit. Table 5 shows that companies that are ethnically closer to their VCs continue to flourish even after IPO: In the model with VC-fixed effects, an additional coethnic pair is associated with, on average, a USD 0.1 million higher market capitalization and USD 0.009 million higher net income one year after IPO for the startups. Thus, we find no evidence that ethnically close VCs and companies "hoodwink" public markets in their IPOs.

### Effect of ethnic proximity on VCs' payoffs

We find that the ethnic proximity of VCs and entrepreneurs is associated with a higher probability of the portfolio investment going public or being acquired. How much is this increased likelihood of IPO or acquisition worth to VCs? Using data and analysis found in Cochrane (2005) we can compute the positive impact of a one percent increase in IPO or acquisition probability on the *ex ante* expected rate of return to be 11 percent. This implies that our conservatively observed increase in the probability of successful exit of 2.5 percent

(Column 2 of Table 4) associated with an additional executive who shares ethnicity with a VC partner increases the expected rate of return by around 27.5 percent at the time of investment. These IRR estimates show that the economic returns of coethnic partnerships are substantial, but should be interpreted cautiously – they rely on Cochrane’s finding that VCs, on average, enjoy 698 percent returns from successful exit events.

### Conclusion

Our previously developed formal model highlights the subtle interaction between the selection and influence effects of social associations in business partnerships. It can be applied to many settings where the association between potential partners can be described with a distance metric. The model proposes that if proximity improves (selection relevant) information and most potential candidates are unsuitable, then increased confidence in their evaluation will cause evaluators to set lower acceptance thresholds over observable quality signals for nearby candidates. If proximity also improves performance *after* the partnership’s formation, then anticipating this, evaluators will drop thresholds for close opportunities further, even to the point that close candidates of lower quality will be accepted. But this is not taste-based discrimination – for these close relationships will perform better on average than distant ones. Thus, agents will target their searches for potential partners nearby and partner disproportionately with social neighbors.

Our empirical analysis confirms the model’s predictions. We show that conditional on investment, ethnic proximity between VCs and company executives is positively related to the probability that the venture exits in an IPO or acquisition, and to post-IPO market capitalization and net income. We also show that VCs are more likely to select ventures led by coethnic executives for investment, and the effect of proximity on investment selection is particularly salient for early-stage startups. Thus, our findings suggest that in the VC industry, favoritism toward one’s ethnic brethren brings superior economic payoffs. According to the National Venture Capital Association (NVCA), “In 2008, [US] venture capital-backed companies employed more than 12 million people and generated nearly USD 3 trillion in revenue (NVCA 2009, p. 2).” If the ethnicity of a single executive can substantially affect the probability of investment from a particular VC, of growing to sale on public markets, and post-IPO income, as we have found,

we can conclude that individuals’ social associations have profound economic consequences.

In our study, ethnic proximity proxies for a complex web of social ties that include linguistic, religious, and many other associations that bind together members of the same ethnic group. Individuals may choose to tap into certain associations borne out of a common ethnicity and not others. In teasing apart the effects of shared location, industry preferences, and educational background from less-distinct aspects of ethnic proximity that plausibly affect investments, we have only taken a first step in identifying the true effects of ethnic proximity and the channels through which they operate.

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