Ancestral Connections and Corporate Alliances:

The Role of Culture in Mitigating Holdup

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Abstract

We study how culture works as an implicit incentive alignment mechanism to mitigate hold-up problems when firms form alliances. We measure ancestral connection between different areas using historical immigration from different countries to the U.S. and demonstrate its role in transmitting exogenous ideological shocks. We show that the ancestral composition of the area where firms locate influences their choices of alliance partners and new venture locations. Further, partners experience significantly better performance when the ancestral connection between their headquarters or between their inventors is stronger. Shared values and beliefs between firms' key stakeholders likely underlie the role of ancestral connection.

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1. Introduction

The theory of the firm started with transaction costs and incomplete contracts. According to standard property rights theory (e.g., Hart and Moore 1990), joint production and shared ownership is suboptimal due to the possibility of holdups, although Holmstrom (1999) points out that this prediction is quite fragile. Recent theoretical literature has suggested that culture can shape firm boundaries, because, at times, implicit norms are more efficient than detailed contracts (Gorton and Zentefis 2020). More broadly, individuals consider their surrounding social and cultural circumstances when making utility-maximizing decisions, and culture ultimately regulates internal governance, production decision, etc. (e.g., Hermalin 2001; Van den Steen 2010; Song and Thakor 2019). Of course, relying on culture (implicit norms) to coordinate efforts entails both potential benefits and costs (e.g., the cost to acquire the knowledge of common "codes"), leaving the importance of culture in organizational economics an empirical question. In this paper, we revisit firms' decisions to form alliances—a decision that changes firm boundaries, and one that also often requires a decision to determine the location of the new venture—and empirically assess the importance of culture in mitigating hold-up problems under incomplete contracts.

In light of the emerging literature emphasizing historical immigration as a seed of Americans' values and preferences, which evolve slowly over time (e.g., Guiso, Sapienza and Zingales 2006; Giuliano and Tabellini 2020; Sequeira, Nunn, and Qian 2020), we focus on how ancestral connection between U.S. firms' stakeholders, as an implicit incentive alignment mechanism, shapes the firms' partnering and location decisions when forming alliances. Different measures of corporate culture in the literature capture varying specific aspects of shared values and beliefs;[1] with ancestral background, we aim to measure the deep root of culture, and in a more general way. Using data from the 1980 Census, the first Census with comprehensive ancestral information, we calculate ancestral distance (the opposite of connection) for a pair of places as the Manhattan (L_1) distance between two vectors characterizing the ancestral compositions of the two places' population. To demonstrate the role of ancestral connection as a channel of shared ideology, we use an exogenous shock to local political ideology due to the entrance of Sinclair, the largest conservative media network in the U.S., in different markets. We find that the local shock propagates through ancestral network to affect political voting outcomes in ancestrally connected but unshocked places.

Alliances are an important corporate organizational form that expands firm boundary.[2] They typically involve cooperative agreements between independent entities and can take the form of a strategic alliance or a joint venture. Shared values and beliefs induced by ancestral connection may play a critical role in alliance formation given the importance of cooperation between partners and the possibility of contractual incompleteness when forming alliances (Robinson and Stuart 2007), which could lead to hold-up problems. In a model where individuals respond to incentives but are also influenced by norms and values inherited from earlier generations, Tabellini (2008) shows that cooperation is easier to sustain if individuals are close (e.g., ethnically) to each other. Finally, the unique feature of choosing both partnering firms and the new venture location, when forming alliances, allows us to test the importance of ancestral connection in shaping firm boundaries from different angles.

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[1] See Gorton, Grennan, and Zentefis (2021) for a literature review on corporate culture, and Aggarwal, Faccio, Guedhami, and Kwok (2016) for a review on culture and finance.
[2] According to the PWC 22nd Annual Global CEO Survey, 40% of U.S. CEOs surveyed planned to develop new strategic alliances or joint ventures in 2019.

We retrieve information on alliance deals announced between 2004 and 2017 from Securities Data Company (SDC) Platinum. Prior literature suggests that prevailing culture in the areas where firms reside, for example local religiosity, affects corporate decisions and outcomes.[3] Focusing on another deep cultural root—the ancestral composition of the local population (Guiso, Sapienza, and Zingales 2006)—we first conduct state-pair-level analysis of alliance activities by examining the number of alliances formed by partners with headquarters in the 1,275 state pairs among all 50 U.S. states plus Washington D.C. over the sample period. We find that a one-standard-deviation decrease in two states' ancestral distance is associated with a 12% increase of alliances, controlling for state fixed effects, similar to the increase in alliances (15%) if the two states are bordering. Using a sample of actual and counterfactual deals, we also find that firms are more likely to partner with firms from ancestrally connected states, especially for alliances in industries that rely more on relationship-specific investments (Nunn 2007) and thus are more subject to the hold-up problem. Further, results from a path analysis suggest that one channel through which ancestral distance affects alliance formation is through ideological distance, measured as the principal component of political distance and religious distance, although ancestral distance has its own, direct effect on alliance formation in addition to this indirect effect.

The key identification strategy in this paper relies on ancestral connection being determined by *historical* immigration patterns and thus not driven by *current* economic conditions. One might worry that such immigration patterns correlate with contemporaneous *historical* economic conditions, which could shape economic outcomes today independently of ancestral connection. To mitigate this concern, we exploit exogenous variation in immigration to U.S. cities,

[3] See, e.g., Hilary and Hui (2009), Adhikari and Agrawal (2016), McGuire, Omer, and Sharp (2012), and Jiang, John, Li and Qian (2018).

induced by WWI and the 1921 and 1924 Immigration Acts. These shocks altered migration flows to the U.S. from different sending regions to different degrees. They thus also unexpectedly altered the number and the mix of immigrants in U.S. cities. Following Tabellini (2020), we construct a "leave out" version of the shift-share instrument commonly used in the labor literature (Card 2001) by apportioning flows from each sending region to a city net of the individuals who eventually settled in that city. Section 4.3 provides details of the instrument's construction and shows how it measures the supply-push component of immigrant inflows to a particular city that is arguably exogenous to local demand. We find that a one-standard-deviation increase in ancestral distance between two cities, driven by the immigration shocks between 1910 and 1930, decreases the number of alliances by 0.14 during 2004 to 2017, compared to its sample mean of 0.07, after controlling for city and state-pair fixed effects.

For a small subset of deals with only public partners, we find that ancestral distance correlates significantly and negatively with abnormal returns around the announcements of alliances, whereas geographic distance does not have a significant effect.[4] One possibility is that lower ancestral distance facilitates coordination and cooperation between employees of partners when forming and operating the new alliance. Another possible, non-exclusive channel is that stockholders, many of whom are local (e.g., Coval and Moskowitz 1999), welcome alliances formed between partners with low ancestral distance, either due to lower information friction or innate preferences (e.g., Ayers, Ramalingegowda, and Yeung 2011).

The literature on how connections affect corporate decisions mainly focuses on professional and social connections among corporate leaders (e.g., Cai and Sevilir 2012; Ishii and

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[4] Similarly, we find a negative effect of ancestral distance on change in combined accounting performance after the deal.

Xuan 2014). Our study highlights the importance of ancestral connection in reducing frictions between stakeholders. Using data on the ancestral origins of inventors, we find that the ancestral distance between inventors at partnering firms is negatively related to announcement abnormal returns. However, this is only the case for R&D alliances, where collaboration between inventors is likely important. We also find that the positive effect of ancestral connection between headquarters states of partners or between inventors is not attenuated when controlling for ancestral and social connections between partners' corporate leaders. Although these findings are only suggestive due to the limited sample size of this analysis, they hint at a distinctive channel of influence from ancestral connection, potentially through non-executive employees and stakeholders.

In addition to the partnering decision, another important alliance decision is the location of the new venture. Over 70% of new ventures are located in one of the partners' states. However, when the partners have larger ancestral distance, they are significantly less likely to place the new venture in the same state as a partner, controlling for partnering states' fixed effects. Interestingly, when the new venture is located outside of the partners' states, which increases the average geographic distance to both partners, the ancestral distance between the venture and the partners is significantly less than the ancestral distance between the partners, suggesting that ancestral distance may play a greater role when partners need a "middle" ground. Finally, for ventures located outside of the partners' states, we use a simple model to "predict" the location of ventures. For each of the actual location and 50 counterfactual locations for any given alliance, we calculate average ancestral distance from partners' locations and then use it to predict the actual venture location. We find a significantly negative relation between the two, suggesting that new ventures are located in places with lower ancestral distances from the partners' states above and beyond geographic distance.

Prior literature has focused on the importance of geographic proximity in corporate and information acquisition, internal resource allocation, and corporate governance (e.g., Kang and Kim 2008; Chhaochharia, Kumar, and Niessen-Ruenzi 2012; Giroud and Mueller 2015; Levine, Lin, and Wang 2020; Heese and Pérez-Cavazos 2020).[5] In a high-immigration country like the U.S., ancestral connections among people extend beyond geographic boundaries and could contribute to shared beliefs and preferences, which in turn facilitate cooperation.[6] In an experiment conducted with Harvard undergraduates, Glaeser, Laibson, Scheinkman, and Soutter (2000) find evidence that racial and nationality differences reduce trust. Our results with field data highlight the importance of studying cultural determinants of firm boundary and location beyond geographic borders.

A seminal paper by Guiso et al. (2006), recognizing the challenges and advances in the literature on culture as a determinant of economic phenomena, suggests using deep aspects of culture that are inherited (e.g., ancestral origin) rather than voluntarily accumulated, as exogenous variables. Alesina and La Ferrara (2005) survey the literature documenting both the positive and negative effects of ethnic diversity on economic outcomes.[7] Pan, Siegel, and Wang (2017) infer

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[5] Ellahie, Tahoun and Tuna (2017) study cross-country differences in beliefs and values and how they influence CEO pay. Erel, Liao, and Weisbach (2012), Ahern, Daminelli, and Fracassi (2015), and Ahmad, de Bodt, and Harford (2020) study (or control for) the effect of cultural distance, among other things, on cross-border mergers. The benefit of the international studies is stronger heterogeneity in cultural values. The benefit of exploring ancestral differences in the U.S. setting, is to effectively control for other institutional or economic differences, while also capturing the deep root of cultural differences within the U.S. Further, we focus on corporate alliances, to study the role of culture in mitigating holdups, which do not exist with full integration through M&As.

[6] Our paper thus contributes to the new paradigm of social economics and finance (see Hirshleifer's 2020 AFA presidential address).

[7] Using directors' ancestral origins to proxy for their opinions and values, Giannetti and Zhao (2019) study the costs and benefits of diversity in the boardroom. Gompers, Mukharlyamov, and Xuan (2016) find that venture capitalists with the same ethnic, educational, or professional background are more likely to syndicate with each other, but that yields worse performance.

corporate risk culture using corporate officers' ancestral background and study its effect on corporate risk taking. We establish the importance of ancestral connection in transmitting ideology shocks and demonstrate that ancestral connection between firms, especially between firms' non-executive employees, is a deep cultural root of firm boundaries and location choices, above and beyond connections between firms' corporate leaders.

One thread of the "culture and economics" literature specifically studies the role of culture in mitigating frictions. Bhagwat and Liu (2020) show that analysts inherited trust attitudes affect their information processing of outside sources. Fisman, Paravisini, and Vig (2017) study the effect of cultural proximity between borrowers and lenders on loan outcomes. Using the location of Japanese internment camps in the U.S. during World War II as an exogenous shock to local ethnic populations, Cohen, Gurun, and Malloy (2017) find that firms headquartered in former-internment areas export significantly more to Japan today than other firms. Our results highlight the role of ancestral connections, both between local communities where firms reside and between their key employees, as an implicit incentive alignment mechanism that could mitigate the hold-up problem.

2. Data and Sample

2.1. Ancestral connection

To capture ancestral connection, we measure the ancestral distance between two places (states, counties, or cities), using the 1980 Census data, the first Census with comprehensive ancestral information. We use the 138 ancestry groups listed by Census (see Appendix 1) and calculate the fraction of population in each ancestry group for each place. We collect the ancestral fractions in a vector (x_1, x_2, …, x_{138}) for each place x and calculate *Ancestral Distance* between two places *x* and *y*, as the Manhattan distance between their ancestral vectors:[8]

[8] Our results are robust to using the Euclidean (L_2) distance as discussed in section 3.1.

$$Ancestral\ Distance_{x,y} = \sum_{i=1}^{138} |x_i - y_i|$$

Theoretically, *Ancestral Distance* may range between [0, 2]. In our sample, it ranges between [0.08, 1.66] at the state level. Table 1 shows that the average *Ancestral Distance* is 0.91 and its standard deviation is 0.32. In Figure 1, we plot the most common ancestry group with the greatest fraction of population in each U.S. state. There are eight ancestry groups that are at the top in at least one state: Afro-American, American Indian-Eskimo-Aleut, English, German, Irish, Italian, Japanese, and Other Spanish. Among all states, the highest fraction of a state's population represented by its most common ancestry group is in Utah with English origin representing 53% of the state's population, while the lowest are in New York and New Jersey, where the most common ancestry group is Italian representing 18% of each state's population. Figure 2 shows the *Ancestral Distance* between Utah and all other states. Darker color represents a greater ancestral distance. The first two figures together suggest that the ancestral composition of Utah is more similar to those of states where the most common ancestry group is also English. However, note that *Ancestral Distance* considers all 138 ancestry groups and does not simply reflect the most common ancestry group of a state. For example, Florida and Oregon's most common ancestry groups are both English, but the *Ancestral Distance* between Utah and Florida is much larger than that between Utah and Oregon. We also construct *Ancestral Distance* in a similar fashion at the county and city level.

Further, we use data from the 2000 and 2010 Census, which report 71 and 103 ancestry groups, respectively, and construct two additional measures of *Ancestral Distance*. The pair-wise correlations among the three measures using the three decennial Census range from 71% to 86%. We will revisit these measures in Section 3.1, when studying the effect of ancestral distance on alliance formation.

The main premise underlying our hypotheses is that ancestral connection influences the degree of shared values and beliefs between two places so it can work as an implicit coordination mechanism. To demonstrate that ancestral connection influences the degree of shared values and beliefs between two places, we examine the role of ancestral connection in transmitting shocks to political ideology. We use political ideology as an example of shared values for several reasons. First, a growing finance literature highlights political ideology as a deep root factor in determining both corporate and investment decisions (e.g., Di Giuli and Kostovetsky 2014; Fos, Kempf, and Tsoutsoura 2021; Hong and Kostovetsky 2012; Cookson, Engelberg, and Mullins 2021). Second, economics literature establishes that historical immigration to the U.S. has long lasting impact on American political ideology, as immigrants brought with them their preferences for welfare and redistribution (Giuliano and Tabellini 2020). Third, while culture is typically slow-moving, recent political literature has identified a good shock to local political attitudes. We conduct a test using the staggered entrances of Sinclair, the largest conservative news network, to various media markets in the U.S. through acquisitions of local TV stations. A seminal paper, Martin and McCrain (2018), documents that these acquisitions were not driven by local economic conditions, but led to a significant rightward shift in the ideological slant of coverage. To examine the effect of ancestral connection in propagating this ideological shock, we estimate the following equation for county *i* at time *t*:

$$\begin{aligned}\Delta Republican\ share_{it} = \alpha_0 &+ \beta_1 \Delta Sinclair_{it} + \beta_2 \Delta AC\ weighted\ Sinclair_{it} \\ &+ \beta_3 \Delta Geo.weighted\ Sinclair_{it} + \beta_4 \Delta FB\ weighted\ Sinclair_{it} \\ &+ \epsilon_{it}\end{aligned} \tag{1}$$

We collect data from six presidential elections between 1996 and 2016. For each election, we calculate the fraction of votes for Republican candidates in each of the 3,104 counties. The dependent variable is the first difference in the Republican voting share from the last election cycle. We then try to explain the change in Republican shares based on whether Sinclair entered the local media market, or media markets in connected counties. The variable *Sinclair* is an indicator variable for whether Sinclair has entered the county during an election cycle.[9] We then take the first difference to get *ΔSinclair*. *ΔAC weighted Sinclair* uses the ancestral connection (two minus ancestral distance) between county pairs to weigh the indicator variable *ΔSinclair* for all other 3,103 counties. Further, we control for *ΔGeo. weighted Sinclair* (in column (4)) or *ΔFB weighted Sinclair* (in column (5)), which use the inverse of geographic distances and Facebook connections (see Bailey, Cao, Kuchler, Stroebel, and Wong (2018) for details) between county pairs as the weights, respectively.[10] We control for state-year fixed effects to absorb any contemporaneous shocks (e.g., policy changes) to the state.

Table 2 reports the results. First, local entrance of Sinclair has a significant and positive effect on the Republican voting share, consistent with the findings in the literature. More interestingly, whether Sinclair entered ancestrally connected counties has an additional significant effect on the change in Republican shares. This result highlights the role of ancestral connection in transmitting ideology shocks: even if Sinclair didn't directly enter a local media market, the political attitudes in a place could be influenced by Sinclair entries in its ancestral network. Further, the effect of ancestral connection cannot be explained by geographic distance or Facebook connections. Therefore, the transmission mechanism is more likely to be other social interactions. Finally, our results are robust to using county and year fixed effects instead, although this

[9] 7.2% of the county-years in our sample had Sinclair entry, while exit was rare (only 0.7%).
[10] While this measure is only available based on Facebook connections in 2018, Bailey, Gupta, Hillenbrand, Kuchler, Richmond and Stroebel (2021) show that social connectedness as measured today predicts trade flows in the 1980s as well as it predicts trade flows today.

alternative specification is associated with a smaller economic magnitude for *ΔAC weighted Sinclair*. While prior research focuses on the cross-sectional variation in ancestral values and beliefs that immigrants brought from their home countries, our analysis exploits time series shocks to local ideology and highlights the role of transmitting shocks via ancestral network as another reason why values and beliefs are often shared between ancestrally connected places.

2.2. Sample

We gather information about alliances, from the SDC Platinum database, which leads to 10,868 deals formed between two partners located in the 50 U.S. states plus D.C., announced between 2004 and 2017. Among these deals, 17% are formed as joint ventures, while the remainder are strategic alliances. Further, 8,434 alliances are formed by partners with different headquarters states. We focus on this main sample in most of our analysis, as they allow us to potentially separate the effects of cultural and geographic determinants of firm boundary. However, since the analysis of announcement abnormal returns further restricts the sample to 901 deals with public firms,[11] we include deals with same-state partners in some specifications without other controls.

We also use the 1980 Census to construct state-level measures that capture local demographic information: the median age of the state's population, the fraction of females in the state's population, the fraction of people at least 25 years old who have at least a bachelor's degree. We use the absolute difference between these measures to construct state-pair-wise control variables—*Age_diff*, *Female_diff*, and *College_diff*.

To measure geographic distance between two states, we construct two variables. *Border* is an indictor variable that equals one if the two states share border. *Geographic Distance* is the

[11] Announcement abnormal returns of deals are calculated as the market value weighted announcement abnormal returns to both partners as discussed in section 4.1. When the return data is only available for one partner, its announcement abnormal return is used to measure the announcement abnormal return of the deal.

geographic distance between two states' capital cities, based on data retrieved from https://demographicdata.org/distance-charts/distance-data/. Another important control variable is the difference between two states' industry compositions. To measure industry composition, we focus on public firms that report business addresses and SIC codes in their annual reports (10-Ks) filed with the SEC. We calculate the market value weighted fraction of firms in each 2-digit SIC industry for each state year. We then calculate *Ind_diff* annually, for each state pair, as the Manhattan distance between state vectors of these fractions.

We also collect data to measure various aspects of social and cultural connections, in particular those related to ideology. To measure political distance between two states, we collect data from the four presidential elections during our sample period (2004, 2008, 2012, 2016). For each election, we calculate the fraction of votes for Democratic, Republican, and Independent (or Other) candidates in each state to form the voting vector and then calculate the Manhattan distance of voting vectors between each pair of states. We take the average distance across the four elections for each state pair to construct *Polit_distance*.

To measure religious distance, we collect data on religious affiliations from the Religious Congregations and Membership Study. It is part of the U.S. religion census, designed and carried out by the Association of Statisticians of American Religious Bodies (ASARB) in 2010, the only year for which we have data during our sample period. The study reports a total of 344,894 congregations with 150,686,156 adherents, comprising 49% of total U.S. population in 2010. It also reports the rate of adherence to each denomination in each state (scaled by the state's population). We use the vectors of rate of adherence to top ten religions to calculate the Manhattan distance as religious distance between two states (*Relig_distance*).[12] We then extract the first principal component of *Polit_distance* and *Relig_distance* as *Ideology_distance,* with an eigenvalue of 1.3.

To measure ancestral distance between patent inventors of partner firms, we collect data on inventors of patents awarded by the U.S. Patent and Trademark Office (USPTO) from www.patentsview.org. We use the Global Corporate Patent Dataset to link patents awarded by the USPTO and public U.S. firms.[13] We define an inventor's employer as the patent's assignee following Fitzgerald and Liu (2020). We use inventors' last names to infer their ancestral origins following Liu (2016) and Pan, Wang, and Siegel (2017, 2020). We then calculate the fraction of each ancestry among all inventors associated with the firm over the three years prior to the year of alliance announcement, collect the fractions in vectors, and calculate *Ancestral Distance_inventors* as the Manhattan distance between the vectors.

Finally, we collect information on corporate leaders from BoardEx. We again use their last names to infer their ancestral origins. We construct an indicator variable *Same origin_CEO* that equals one if the CEOs of both partners in the deal have the same ancestral origin. We also calculate the fraction of each ancestry among members of each board (including the CEO), collect the fractions in vectors, and calculate *Ancestral Distance_Board* as the Manhattan distance between these ancestral vectors. Following Fracassi and Tate (2011), we construct connection measures between partners' CEOs (*Ties_CEO*) and between partners' boards (*Ties_Board*), based on the number of ties (professional, education, and other activities) they share.

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[12] See the list of top 25 U.S. churches based on data collected by the churches in 2010 and reported in the 2012 Yearbook of American & Canadian Churches here: http://www.ncccusa.org/news/120209yearbook2012.html

[13] We thank Jan Bena, Miguel A. Ferreira, Pedro Mato, and Pedro Pires for sharing the Global Corporate Patent Dataset. See Bena, Ferreira, Matos and Pires (2017) for detail of techniques used to match USPTO patents to firms.

Table 1 reports the descriptive statistics of the main sample. The average number of alliances between two states in the U.S. is 7.32 and the median is 1, which suggests that variable *Count* is very skewed. We take the natural logarithm of (1+*Count*) to mitigate the effect of skewness. 72% of alliances are located within the same state as at least one of the partners. In 12% of deals in the sample, partners are from states border each other. The mean abnormal announcement return is 0.35%, which is significantly different from zero.

3. Ancestral distance and alliance activities

Forming alliances enables firms to diversify or generate synergy by combining complementary strengths and provides firms with a flexible alternative to organic growth or mergers. It also allows firms to navigate new territories in the product space or geographic markets (Mody 1993; Das, Sen, and Sengupta 1998; Robinson 2008; Li, Qiu, and Wang 2019). However, firms could be discouraged to form alliances as they face the hold-up problem when relationship-specific investments are needed. The role of culture, as implicit norms, could be particularly important when cooperation is needed but it is impossible or expensive to design (or enforce) complete contracts, which is the case when forming alliances. As a result, announcements of alliance formation often emphasize the role of cultural fit.[14]

Prior research finds that decisions by individuals and firms reflect local social norms and beliefs where they reside, especially where their headquarters reside (see, e.g., Hilary and Hui 2009; Shu, Sulaeman, and Yeung 2012; McGuire et al. 2012; Di Giuli and Kostovetsky 2014; Hasan, Hoi, Wu, and Zhang 2017; Hayes et al. 2019; Hoi, Wu, and Zhang 2019; Pan et al. 2020; Dass, Nanda, and Xiao 2020). Similarity in local culture where partnering firms reside, shaped by

[14] For example, in the announcement of a joint venture between Atlas Real Estate and DivcoWest, cultural fit was mentioned as a key factor to the decision of forming alliance. See https://www.multihousingnews.com/post/atlas-real-estate-divcowest-form-1b-sfr-joint-venture/

historical immigration, could thus lead to shared beliefs and preferences between partnering firms' stakeholders, which mitigate the hold-up problem by reducing information friction and facilitating cooperation. We test the effect of ancestral connection on alliance formation in this section.

3.1. State-level analysis

In Figure 3, we plot the heat map of the numbers of alliances between state pairs in the upper triangle and ancestral connections between state pairs in the lower triangle. Darker (lighter) color represents less (more) alliances or connections between two states. To facilitate comparison, we sort states based on their average connections to all other states, so states with fewer ancestral connections (e.g., Hawaii) are in the bottom left corner. The similarity in color patterns in the upper and lower triangles suggest a positive relation between alliance activities and ancestral connection. Some states, such as California, have more alliances and better ancestral connections in general. Other states, such as those in the upper right corner of the graph, exhibit some segmentations in alliance activities potentially due to higher ancestral connections among themselves.

To test the relation between ancestral connection and the formation of alliances, we estimate the following model:

$$Count_{ij} = \alpha_0 + \beta_1 Ancestral\ Distance_{ij} + \beta_2 Border_{ij} + \beta_3 Geographic\ Distance_{ij}$$
$$+\beta_4 Ind\_diff_{ij} + \beta_5 Female\_diff_{ij} + \beta_6 Age\_diff_{ij} + \beta_7 College\_diff_{ij} + \epsilon_{ij} \quad (2)$$

where subscripts i and j denote the two states in the pair. We form 1,275 distinct state pairs among all 50 states plus the D.C. We control for *Border* and *Geographic Distance* because prior studies show that geographic distance is associated with corporate investment decisions (e.g., Kang and Kim 2008). We include the difference in industry composition in the model so that our results are not driven by two states' industrial relation (Robinson 2008). We also control for difference in other demographic characteristics between the two states, *Female_diff*, *Age_diff*, and *College_diff*.

We (double) cluster standard errors by states to mitigate potential correlations among error terms within the clusters.

It is plausible that there may exist unobserved state heterogeneity (e.g., tax rates) that can potentially affect the alliance activities. Therefore, we include state fixed effects, separately for both states in the pair, when estimating the model. Any other potential omitted variable (e.g., economic relation) will have to be at the *state-pair* level. We will further address the identification issue in section 3.3, but would like to note that ancestral distance, based on historical immigration, is a deep and persistent cultural aspect (Guiso et al. 2006). Thus, many of these state-pair-level variables are more likely to be (at least partially) *caused by* ancestral connection, which mitigates the concerns of confounding factors and reverse causality.

Table 3 reports the results. In column (1) we find a significantly negative coefficient on *Ancestral Distance* before we include any control variables or the state fixed effects. It suggests that there is a negative correlation between the number of alliances formed by partners located in a pair of states and the ancestral distance between this state pair. *Count* is highly skewed, so we transform it to *ln(Count)* in column (2) by taking the natural logarithm of *Count* plus one. Even after we control for geographic distance, the difference in industry composition, and state fixed effects, the effect of *Ancestral Distance* remains significantly negative in column (2). Considering that 39% of the state pairs do not have any alliance activities, we re-estimate model (1) after excluding those state pairs with no alliance between them to get the intensive margin and find similar results in column (3). To examine whether our results are affected by the dominance of firms incorporated in Delaware (the "Delaware effect"), we also re-estimate the model after excluding Delaware firms, and the results in column (4) are very similar to the results estimated with the full sample in column (3). Finally, we control for differences in other demographic characteristics in column (5) and the results remain consistent. We find that a one-standard-deviation decrease in two states' ancestral distance is associated with a 12% increase of alliances, similar to the increase in alliances (15%) if the two states border each other.

Although it is hard to pin down the exact channel for the effect of ancestral connection, we revisit the hypothesis that it may influence the degree of shared ideologies, and therefore collaboration between local employees (and between stakeholders, generally speaking) of the partnering firms. Giuliano and Tabellini (2020) document that historical immigration to the U.S. is associated with political ideology today. In Section 2.1, we demonstrate the role of ancestral connection in transmitting shocks to local political ideology. To examine if shared ideology could indeed be one channel through which ancestral connection affects alliance formation, we construct *Ideology_distance*, using the principal component of political distance and religious distance, and conduct a path analysis. Figure 4 plots both the direct effect of ancestral distance on alliance formation, and its indirect effect through *Ideology_distance*. Both effects are significant, which suggest that ancestral connection could facilitate alliance formation through shared ideologies, but may also have a direct effect.

We also perform several additional robustness tests. First, we examine whether results are driven by states with large ancestral distances from other states, including DC, HI, SD and ND. After further excluding these states, in Appendix 3 column (1), we continue to find similar results as those in Table 3 column (3). Second, we check the robustness of our findings to including additional controls for the absolute difference in concentrations of ancestral composition (*HHI_diff*) and in state corporate tax rates (*Tax_diff*) between the partners' headquarters states. In Appendix 3 column (2), we find that the results are unaffected. Third, we re-calculate *Ancestral Distance* based on 10 broader ancestry groups of the 1980 Census (see, Appendix 1 Panel B), considering the possibility that ancestry groups from the same broader category might have similar culture or more trust towards each other (Bornhorst et al. 2004). We find, in Appendix 3 column (3), consistent results using the ancestral distance calculated based on the broader ancestry categories as those in Table 3. Fourth, in Appendix 3 column (4), we report a specification using the 2010 Census instead of 1980 Census. Results remain similar. Fifth, we report results using L2-norm distance measures instead of L1-norm measures, in Appendix 3 column (5). We focus on L1-norm measures in this paper, since L2-norm measures tend to magnify the effect of outliers. Still, we find quantitative similar results using L2-norm measures.

Further, we examine whether ancestral distance affects a firm's partnering decision at the deal level. For any given partner in an actual deal, we form counterfactual deals by selecting counterfactual partners that have not formed alliances over the three-year period centered around the year of the deal, and are from the same four-digit SIC industry but different state as the actual partner of the focal firm. We also require the counterfactual partner's size (measured as total assets) to be between 50% and 150% of the actual partner's size (Li, Qiu, and Wang, 2019). We test whether ancestral distance between the states of the partners (actual or counterfactual) is correlated with the probability of being an actual pair of alliance partners.

In Table 4 we find that ancestral distance is negatively correlated with the partnering decision after controlling for the deal fixed effects. Firms are more likely to partner with another firm that is from a state with lower ancestral distance, consistent with the findings from the state-level alliance intensity analysis. For a one-standard-deviation decrease in *Ancestral Distance*, the probability of forming an alliance increases by 1.7%, compared to the unconditional probability of forming alliances (9.5%) in this sample. In columns (3) and (4), we partition the sample based on the median of *Relationship-specific Investment*, which is measured following Nunn (2007) to capture the degree of relationship-specific investment required for inputs in each industry. We find that the effect of *Ancestral Distance* is driven by alliances from industries that rely more on relationship-specific investment and hence are more likely to suffer from the hold-up problem.

We also consider the possibility that differences in firm characteristics between actual and counterfactual partner pairs might affect alliance formation. To address this issue, we measure the absolute difference in the following firm characteristics between each partner pair: capital expenditure, R&D, return on asset, cash holding, Tobin's Q, financial leverage, total assets, and sales growth (Li, Qiu, and Wang, 2019). We then use entropy balancing to re-weight the observations of the matching sample such that the mean of these covariates is balanced between the actual and counterfactual partner pairs. In Appendix 4, we continue to find that *Ancestral Distance* is significantly and negatively related to alliance formation, after entropy balancing of firm characteristics that might influence alliance formation.

3.2. County-level analysis

We also constructed the ancestral distance measure at the county level where partnering firms' headquarters reside. Which level of aggregation is more appropriate depends on two factors. First, whether key stakeholders (e.g., employees) and stockholders likely come from the entire state, or are more concentrated locally. Second, whether stake- and stock-holders' beliefs and preferences are more likely to be shaped by local culture at the narrower or broader level. There is no definitive answer to these questions, so we conduct a robustness check of the analysis in Table 3 at the county level. Results are reported in Table 5.

The first three columns in this table use the whole sample (3,136 counties) to construct county-pair observations. Columns (1) and (2) control for whether the two counties are adjacent, or whether they are in the same state, as well as county fixed effects. Column (3) also controls for state-pair fixed effects, which is not possible in the previous analysis at the state level and further rules out any omitted variables at the state-pair level. As before, we find a significant and negative correlation between county-level ancestral connection and the number of alliances formed between the two counties. The large number of county-pair observations highlights the challenge of dimensionality with finer-level analysis. In the last two columns, we focus on the intensive margin with a much smaller sample of county pairs that had formed at least one alliance during our sample period, and find similar results.

3.3. Historical immigration shocks

The key identification strategy in this paper relies on ancestral connection being determined by historical immigration patterns. One potential concern is that both historical immigration and economic outcomes today could be correlated with historical economic conditions in different places (e.g., job opportunities). To mitigate this concern, we exploit exogenous variation in immigration to U.S. cities, induced by WWI and the 1921 and 1924 Immigration Acts (Tabellini 2020), to construct a city-level ancestral connection measure that is exogenous to historical economic conditions.

As Tabellini (2020) explains in detail, WWI and the Immigration Acts affected migration flows to the U.S. from different sending regions, with varying cultural background (e.g., language or religion), to different degrees. These cross-country differences generated significant variation in, and unexpectedly altered the number as well as the mix of immigrants into the U.S., which is the exogenous variation we exploit here. Following his work, we construct a "leave out" version of the shift share instrument commonly adopted in the labor literature (Card 2001), building on the fact that immigrants' location decision typically follows pre-existing settlement patterns (Stuart and Taylor 2012). Sequeira et al. (2020) document that the gradual expansion of the railway network during the second half of the nineteenth century combined with staggered immigration from different sending countries is a strong predictor of the geographic distribution of immigrants in the U.S. Tabellini (2020) further provides ample evidence that city-specific characteristics that attracted early-movers from a given country and determined the 1900 settlement did not affect local economic and political development in subsequent decades. Essentially, the shift share instrument becomes a measure of the supply-push component of the immigrant inflows to a particular city that is arguably exogenous to local demand conditions, which helps to identify the causal effect of immigrant inflows in the presence of unobserved city-specific demand shocks (e.g., those related to economic conditions). More specifically, this instrument predicts the fraction of immigrants from a given sending country to a given U.S. city, out of the total city population, between 1920 and 1930:

$$Z_{jct} = \frac{1}{PredPop_{ct}} \alpha_{jc} O_{jt}^{-M}$$

where *c* denotes the receiving U.S. city, *j* denotes the sending country, and *t* denotes the 1920 or 1930 Census during the shock period (WWI and the Immigration Acts).[15] The predicted city population (*PredPop*) is constructed by multiplying the 1900 population by average urban growth in the U. S. between Census t and t-1, excluding the Census division where the city is located. α_{jc} is the share of individuals from country *j* that live in city c in 1900. O_{jt}^{-M} is the number of immigrants from country *j* that entered the U.S. between t and t-1, excluding those that eventually settled in city c.

Tabellini (2020) uses this "leave out" version of share shift to instrument for immigration during the 1910-1930 period. For our purpose, we aggregate Z_{jct} by averaging over this period to

[15] We thank Marco Tabellini for providing this data.

get Z_{jc} and collecting Z_{jc} of all sending countries to form a vector Z_c. We then use Z_c to calculate the city-pair-level ancestral connection, for the sample of 180 U.S. receiving cities in Tabellini (2020). In Table 6, we regress the number of alliances between two cities on their ancestral connection driven by WWI and the Immigration Acts. In columns (1) to (3), we use all city-pairs, and find that a one-standard-deviation increase in historical ancestral distance between two cities decreases the number of alliances by 0.14 today, compared to its sample mean of 0.07 (and standard deviation of 0.72), after controlling for city fixed effects and state-pair fixed effects. If the ancestral connection is indeed driven by exogenous immigration shocks, its effect on alliances should be uncorrelated with other variables. This is what we find: adding a "same-state" control and various fixed effects do not change the coefficient on ancestral connections. In column (4), we focus on the subsample of city-pairs with alliances, and find similar results. Overall, the results in this subsection establish a causal relation between ancestral connection and alliance formation. Together, the findings in this section suggest that ancestral connection shaped by historical immigration patterns, could facilitate alliance formation by mitigating the hold-up problem and hence be a deep cultural root for firm boundaries in the U.S. today.

4. Alliance performance

4.1. Ancestral connections and announcement abnormal returns

If ancestral connection indeed induces shared values and beliefs, which mitigates the hold-up problem and facilitates cooperation, we expect better alliance performance formed by partners from well-connected places. In this section, we examine the relation between ancestral distance and the combined abnormal announcement returns of partners. Due to data availability, we focus on deals with two public partners. We measure the combined abnormal announcement returns as the market value weighted abnormal returns to both partners over the window [-1, 1], where day zero is the announcement date. The abnormal announcement returns are calculated as the residuals from the three-factor Fama-French model (Fama and French, 1993) estimated over 100 trading days ended 20 trading days prior to the announcement date. We then estimate the following model:

$$CAR_k = \alpha_0 + \beta_1 Ancestral\ Distance_{ij} + \beta_2 Border_{ij} + \beta_3 Geographic\ Distance_{ij}$$
$$+\beta_4 Ind\_Diff_{ij} + \beta_5 Female\_diff_{ij} + \beta_6 Age\_diff_{ij} + \beta_7 College\_diff_{ij} + \epsilon_k \qquad (3)$$

where i and j denote the states in which the partners reside, and k denotes the deal k. We start with 901 deals with available *CAR*, setting ancestral distance to be 0 for within-state deals.[16] We then focus on cases where ancestral distance is likely to be important—when the friction to cooperate is large, in particular, when the partners are from different states, from different industry, or with large geographic distance.

In column (1) of Table 7, we find a significant and negative coefficient on *Ancestral Distance*, suggesting that the market reacts more positively to alliances formed by partners located in states with closer ancestral connection. One possibility is that lower ancestral distance facilitates coordination and cooperation between employees of partnering companies, leading to successful collaborations in the alliances. Another potential, non-exclusive channel is that stockholders value alliances formed by partners from states of low ancestral distance, either due to lower collaboration friction or their own innate preferences because they are often local. The results hold when we focus on out-of-state deals in column (2), which suggests that the effect does not just capture home bias. A one-standard-deviation decrease in ancestral distance is associated with an increase of abnormal announcement return of 0.26%, roughly 7% of the standard deviation for the abnormal announcement return. Interestingly, the geographic distance between partners does not have a significant, direct effect on announcement abnormal returns.

[16] We do not include state-pair controls, because they will also have to be set to 0 for within-state deals.

We report several robustness checks in the appendices. In Appendix 5, we use different asset pricing models, and a different length of the event window, to estimate abnormal announcement returns. In Appendix 6, we examine the relationship between county-level ancestral distance and announcement returns. Results remain similar. Finally, in Appendix 7, we find that the change in combined operating performance after the deal is also higher when the ancestral distance between the partner states is smaller.

4.2. Non-executive key employees vs. corporate leaders

The labor markets for both executives (Yonker 2017; Ma, Pan, and Stubben 2020) and rank-and-file employees may be geographically segmented. Therefore, ancestral distance between partners' states may capture both the ancestral distance between corporate leaders and between other stakeholders of the partners. To examine the role of stakeholders, we consider the ancestral distance between partners' patent inventors, *Ancestral Distance_inventors*, as defined in Section 2. Since patent inventors are likely more crucial to the success of alliances when the alliance activities are related to R&D, we partition the sample based on whether the alliance is related to R&D activities or not. In Table 8, we find that ancestral distance between inventors is negatively related to announcement abnormal returns only when the alliances are related to R&D activities. The results suggest that ancestral connections between partners are beneficial for the alliance potentially due to shared values and beliefs between key employees of the partners, which is the case with inventors when the alliance focuses on R&D.

Prior literature on how connections affect corporate decisions mainly focused on professional and social connections among corporate leaders (e.g., Cai and Sevilir 2012; Ishii and Xuan 2014). We thus measure the ancestral distance between corporate leaders as well. We include an indicator variable that equals one if CEOs of the partners have the same ancestry origin, *Same*

Origin_CEO, and the ancestral distance between the boards (including the CEOs) of the partnering companies, *Ancestral Distance_Board*, as defined in Section 2. To maximize the sample for this test, we again start with all deals with available announcement abnormal returns and available information on corporate leaders' ancestries, including in-state deals with ancestral distance set to be 0.

In Column (2) and (3) of Table 9 Panel A, we find that *Ancestral Distance* between partners' headquarters continues to have a significant and negative effect on the abnormal announcement returns after controlling for the ancestral distance between the CEOs and the boards. *Same Origin_CEO* has a significant and positive effect while *Ancestral Distance_Board* does not have a significant effect on *CAR*. The results suggest that the effect of ancestral distance extends beyond the ancestral similarity between corporate leaders.

Further, we collect data on corporate leaders' social connections, and control for that by including *Ties_CEO* and *Ties_Board* as defined in Section 2, when testing the effect of ancestral distance on combined abnormal announcement returns. In Column (4), we find that *Ancestral Distance* continues to have a significant and negative effect on abnormal announcement returns. Ties between CEOs have a significant negative effect on *CAR*, while ties between boards do not have a significant effect, in our sample.

Similarly, we consider *Ancestral Distance_inventors* while controlling for the connections between corporate leaders in Column (5). We find a significant and negative coefficient on *Ancestral Distance_inventors* after controlling for the ancestral distance and social ties between corporate leaders. The results corroborate that successful collaborations between firms' stakeholders, such as the inventors, as opposed to connections between corporate leaders, likely underlie the role of ancestral connection.

Next, we focus on out of state deals, which allow us to include additional controls for differences in industry composition and other demographic characteristics between the partners' states. In Table 9 Panel B, after controlling for differences between the partners' states, we find a significant and more negative coefficient on *Ancestral Distance* in column (1) compared to column (4) of Panel A. Similarly, we find that *Ancestral Distance_inventors* continues to have a significant and negative effect on abnormal returns in column (2), after including the additional controls. We then further control for financial characteristics of the partners by including the average *ROA*, *ln(Sales)* and *R&D* of the partners. In columns (3) and (4), we find a significant and more negative coefficient on *Ancestral Distance* and *Ancestral Distance_inventors*, respectively.

Overall, these results suggest that the market expects greater value for alliances when partners are from two states with more similar ancestral compositions, and when key employees are close to each other ethnically, consistent with the implications from the cooperation model in Tabellini (2008). While the sample size for these analyses is limited, we find suggestive evidence that the effect of ancestral distance is distinct from connections between corporate leaders, and potentially through non-executive key employees.

5. Alliance location choice

Another important decision, when firms form alliances, is where to locate the new venture. In our sample, 72% of the alliances are located in one of the partners' states, suggesting the importance of geographic proximity in the location decisions, and to some extent, confirming the relevance of the state variables provided by SDC.[17] Interestingly, on average, when the alliance is located outside both partners' states, the ancestral distance between the alliance's location and the

[17] One empirical concern could be that the variables for partners' states, provided by SDC, simply represent partners' headquarters states, instead of relevant subsidiaries that form alliances. The fact that the majority of the alliances resides in one of the partners' states, based on the same SDC information, mitigates this concern.

partners' locations (0.73) is significantly less than the ancestral distance between the partners (0.79). This result suggests that ancestral distance might play a role in the location decision, when a "middle ground" needs to be found.

In Table 10, we first examine whether the decision to locate the new alliance in the same state as (at least one of) the partners depends on the ancestral distance between the partners. We find that when the partners have larger ancestral distance, they are significantly less likely to place the alliance in the same state of a partner, controlling for partnering states' fixed effects. Maybe surprisingly, we find no evidence that whether partners' states border each other has an effect on the location decision.

For deals with the new venture not located in the partners' states, we then test the effect of ancestral distance on the true location of the alliance against counterfactual locations. For any alliance, there are potentially 51 locations—50 states plus the D.C., which include one real location of the alliance and 50 counterfactuals. For each of the 51 possible locations for any given alliance, we calculate its average ancestral distance from partners' locations, and use it to predict the actual venture locations. We also include the average values of the control variables between the new venture's location and partners' locations. In Table 11, we find a significant and negative correlation between a state's average ancestral distance to both partners' states and the probability to be selected to place the new venture, controlling for states' fixed effects or deal fixed effects. The results suggest that indeed, when the new venture needs to be put outside of both partners' states, possibly because the ancestral distance between partners' states is large, partners are more likely to choose a place with lower average ancestral distance with their states.

When the new venture is located outside of partners' states, the average geographic distance between the partners and the new venture is larger, compared to the case when the new venture is put in one partner's state, by definition. However, firms might feel uncomfortable placing the new venture in partners' headquarters states, especially if the ancestral distance between the two partners is large—which might lead to reduced cooperation or larger informational frictions. In this case, firms seem to go for a "middle ground", finding a third state with low ancestral distance to both partners to locate the new venture, despite on average a greater geographic distance compared to placing it to one partner's home state. This result highlights the importance of cultural determinants in location decisions, more than geographic distance.

6. Conclusion

In this paper, we study how cultural determinants—the ancestral background of a firm's stakeholders—shape firm boundary and location. In particular, we focus on the role of culture as an implicit incentive alignment mechanism to mitigate hold-up problems in alliance formation. We first demonstrate that ancestral connection can be a channel of shared values and beliefs by showing that the ancestral network propagates shocks to local ideology. Next, exploiting immigration to the U.S. cities induced by WWI and the Immigration Acts of the 1920s, we find that ancestral connection driven by the supply-push component of the historical immigration, increases alliance formation today. Partnering firms in an alliance experience significantly higher abnormal announcement returns when the ancestral connection between their headquarters or between key non-executive employees is higher. The performance effect from ancestral connection is distinct from social connections between corporate leaders.

Further, when the ancestral connection between the partnering firms' states is low, the new venture is more likely to be placed in one of the firms' home states. If firms decide to locate the venture outside of their states, however, they tend to choose a place with stronger ancestral connection. Overall, our results highlight the importance of ancestral connection, especially between firms' stakeholders, in mitigating the hold-up problem and shaping firm boundaries, above and beyond geographic boundaries. Our results thus support prior theoretical (e.g., Tabellini 2008) and experimental (e.g., Glaeser et al. 2000) literature on racial barriers to eliciting cooperation.

Broadly speaking, our study provides evidence that historical ancestral heterogeneity continues to play an outsized role in accounting for the heterogenous values and preferences in today's American society, consistent with the literature that the "melting pot" process has been slow at best (e.g., Borjas 1995, Bisin and Verdier 2000, Giavazzi, Petkov, and Schiantarelli 2019). To facilitate better cooperation among their stakeholders, firms should be mindful about the potential frictions that ancestral heterogeneity exacerbates and try to promote inclusive relations within their organizations and with potential business partners.

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Figure 1. Most common ancestry group

This figure plots the most common ancestry group of each state and the D.C. of U.S. The numbers are the fraction of the state's population represented by the most common ancestry group within the state.

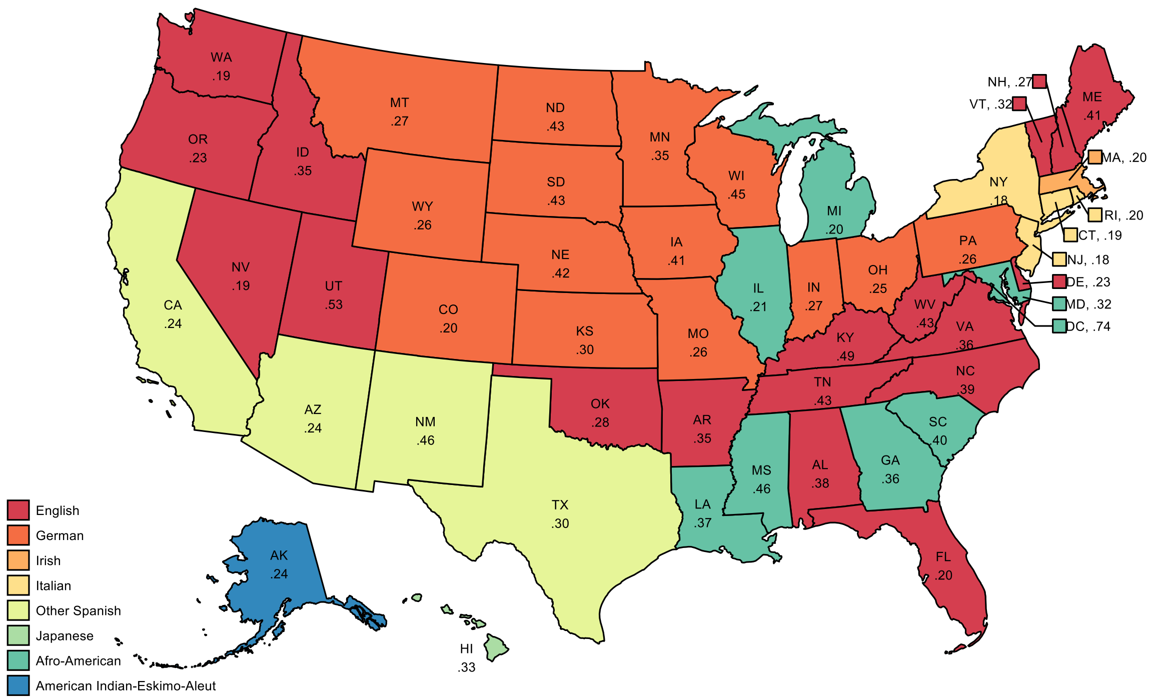

Figure 2. Ancestral distance to Utah

This figure graphs the *Ancestral Distance* between Utah and other states and the D.C. of U.S. Darker green represents a larger ancestral distance.

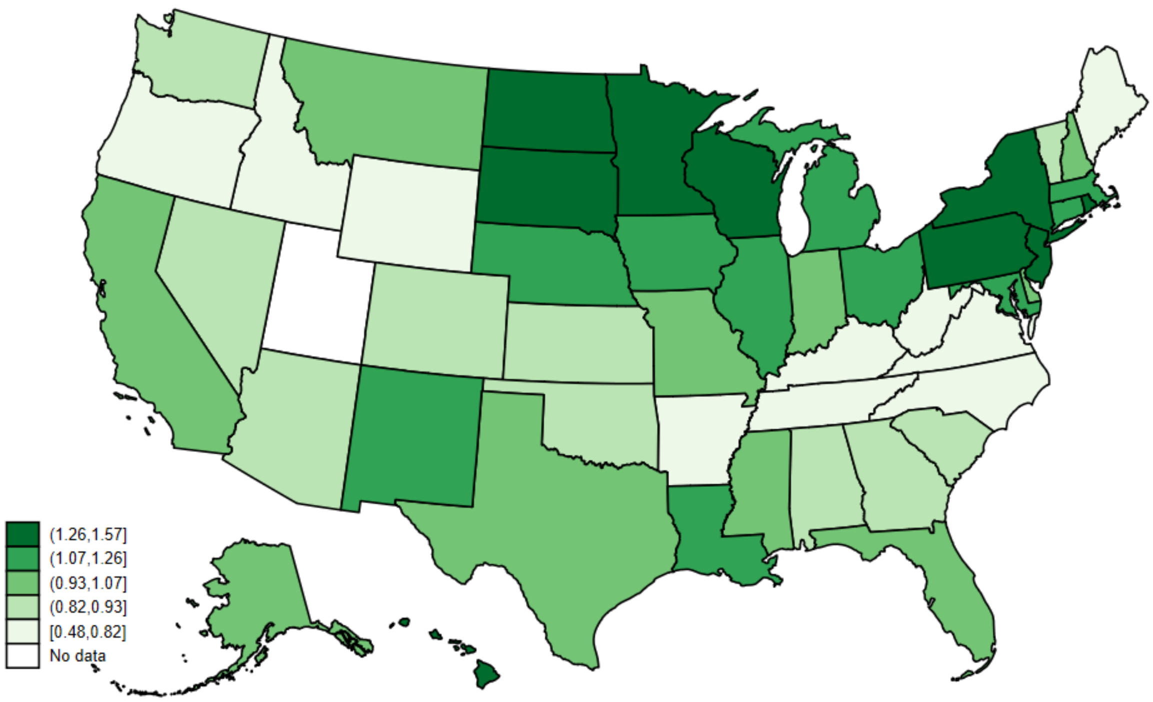

Figure 3. Heat map of alliance counts and ancestral connections

This figure plots the counts of alliances (upper triangle) and ancestral connections (lower triangle) between all state pairs within the U.S. Alliance counts and ancestral connections are ranked into three groups with group three means high alliance counts or high ancestral connections. The states are ordered based on their average ancestral connections with all other states, with Hawaii having the lowest and Missouri has the highest average ancestral connection with other states, respectively.

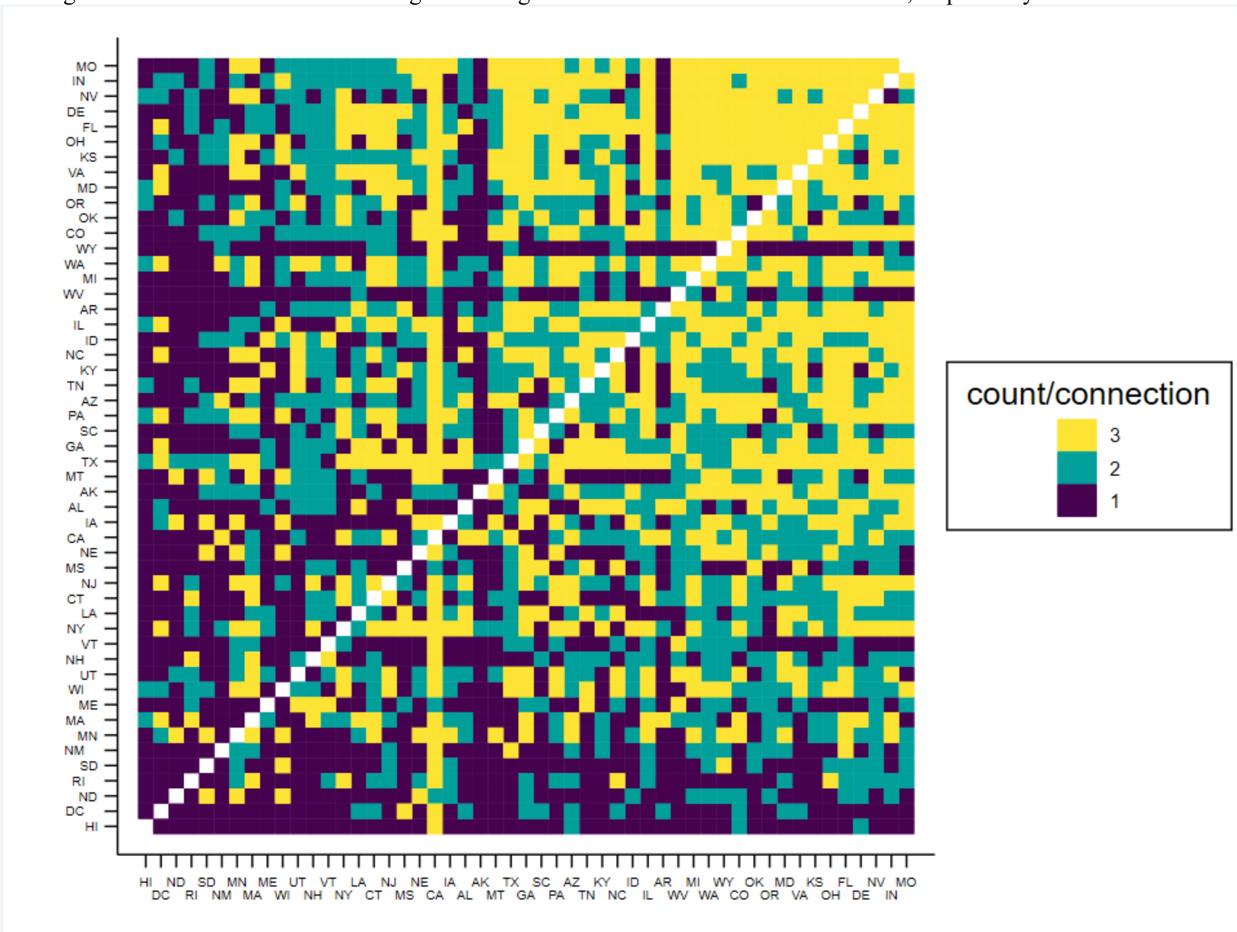

Figure 4. Path diagram

This figure plots the path diagrams of the direct and indirect effects of ancestral distance on ancestral formation. The mediating variable is Ideology distance. Bootstrapped standard errors are reported in parentheses.

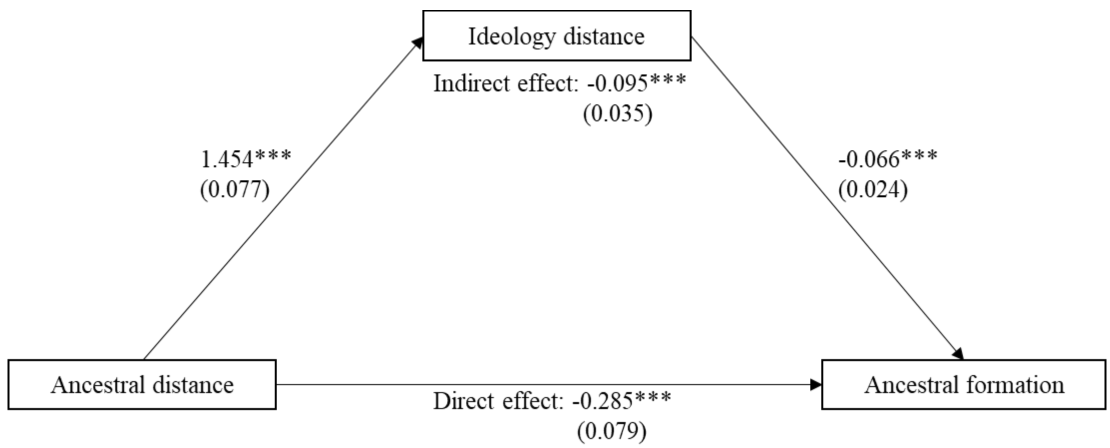

Table 1 . Descriptive Statistics

This table reports descriptive statistics for the variables used in our main analyses. See Section 2.2 for the sample description, and Appendix 2 for a detailed description of the variables.

	Obs.	Mean	Median	Std. Dev.	Min	Max
State-pair variables:						
Count	1,275	7.32	1.00	24.96	0.00	495
ln(count)	1,275	1.09	0.69	1.20	0.00	6.21
Ancestral Distance	1,275	0.91	0.91	0.32	0.08	1.66
Border	1,246	0.09	0.00	0.28	0.00	1.00
Geographic Distance	1,246	1.95	1.60	1.44	0.04	8.24
Ind_diff	1,246	1.68	1.73	0.23	0.81	2.00
Female_diff	1,246	1.10	0.76	1.04	0.00	6.74
Age_diff	1,246	1.82	1.40	1.56	0.00	10.50
College_diff	1,246	3.73	3.14	2.90	0.00	17.04
Deal-level variables:						
Same state (partner and new venture)	8,434	0.72	1.00	0.45	0.00	1.00
Ancestral Distance	8,434	0.78	0.78	0.25	0.08	1.60
Border	8,434	0.12	0.00	0.33	0.00	1.00
Geographic Distance	8,434	2.06	1.72	1.33	0.04	8.19
Ind_diff	8,434	1.43	1.45	0.26	0.66	2.00
Female_diff	8,434	0.01	0.01	0.01	0.00	0.06
Age_diff	8,434	1.78	1.60	1.52	0.00	10.50
College_diff	8,434	0.03	0.03	0.02	0.00	0.17
CAR	901	0.35%	0.26%	3.48%	-17.78%	23.32%

Table 2. Ancestral distance and political attitudes

This table reports coefficient estimates and standard errors from regressions of change in pollical attitudes on Δ*AC weighted Sinclair* and control variables. Δ*Political attitudes* is the change in a county's shares of votes for the republican candidates in a presidential election t from the last election t-1. The sample includes five presidential election data over 2000 to 2016. Specifically, we estimate the following model using pooled regressions with state fixed effects:

$$\Delta Republican\ share_{it} = \alpha_0 + \beta_1 \Delta Sinclair_{it} + \beta_2\ \Delta AC\ weighted\ Sinclair_{it} + \beta_3 \Delta Geo. weighted\ Sinclair_{it} + \beta_4 \Delta FB\ weighted\ Sinclair_{it} + \epsilon_{ij}$$

Standard errors clustered by county are reported in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively. See Appendix 2 for descriptions of variables.

	(1)	(2)	(3)	(4)	(5)
Dependent	Δ*Republican share$_{it}$*	Δ*Republican share$_{it}$*	Δ*Republican share$_{it}$*	Δ*Republican share$_{it}$*	Δ*Republica n share$_{it}$*
Δ*Sinclair$_{it}$*	0.003**	0.007***	0.007***	0.005***	0.011**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.005)
Δ*AC weighted Sinclair$_{it}$*			0.462***	0.442***	0.472***
			(0.108)	(0.108)	(0.109)
Δ*Geo. weighted Sinclair$_{it}$*				0.037	
				(0.031)	
Δ*FB weighted Sinclair$_{it}$*					-0.006
					(0.007)
Year FEs	Yes				
State-year FEs		Yes	Yes	Yes	Yes
County cluster	Yes	Yes	Yes	Yes	Yes
Observations	15,518	15,518	15,518	15,518	15,518
Adjusted R-squared	0.532	0.746	0.746	0.746	0.746

Table 3. Ancestral distance and alliance formation

This table reports coefficient estimates and standard errors from regressions of count of alliances on *Ancestral Distance* between each state pair and control variables. Specifically, we estimate the following model using pooled regressions with state fixed effects:

$$Count_{ij} = \alpha_0 + \beta_1 Ancestral\ Distance_{ij} + \beta_2 Border_{ij} + \beta_3 Geographic\ Distance_{ij} + \beta_4 Ind\_Diff_{ij} + \beta_5 Female\_diff_{ij} + \beta_6 Age\_diff_{ij} + \beta_7 College\_diff_{ij} + \epsilon_{ij}$$

The sample includes all deals with partners from different states. Standard errors double clustered by states of each pair are reported in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively. See Appendix 2 for descriptions of variables.

	(1)	(2)	(3)	(4)	(5)
Dependent	*Count*	*ln(count)*	*ln(count)*	*ln(count)*	*ln(count)*
			count>0	excl. DE	
Ancestral Distance	-9.859**	-0.395***	-0.469***	-0.392***	-0.358***
	(4.601)	(0.119)	(0.152)	(0.119)	(0.112)
Border		0.163***	0.113*	0.153***	0.144***
		(0.050)	(0.057)	(0.051)	(0.042)
Geographic Distance		-0.050*	-0.032	-0.062**	-0.013
		(0.027)	(0.024)	(0.026)	(0.031)
Ind_diff		-0.876***	-0.689***	-0.921***	-0.865***
		(0.140)	(0.170)	(0.139)	(0.139)
Female_diff					-0.051
					(0.041)
Age_diff					-0.064**
					(0.027)
College_diff					-0.029*
					(0.015)
State FEs		Yes	Yes	Yes	Yes
Double cluster	Yes	Yes	Yes	Yes	Yes
Observations	1,275	1,246	770	1,197	1,246
Adjusted R-squared	0.015	0.799	0.798	0.801	0.803

Table 4. Propensity of forming alliance

This table reports coefficient estimates and standard errors from OLS regressions of actual alliance partners on *Ancestral Distance* between partners' states and control variables using a match sample. The dependent variable is an indicator that equals one if the partners are the actual partners of a deal and zero otherwise. For any given firm in the alliance sample, we form counterfactual deals by selecting counterfactual partners that have not formed alliances within the three-year window centered around the year of the deal, are from the same four-digit SIC industry but different state as the actual partner of the focal firm, and have a firm size within 50% to 150% of the actual partner of the focal firm. The sample includes all deals with partners from different states. In columns (3) and (4), the sample is partitioned based on the median level of *Relationship-specific Investment* for an industry, measured following Nunn (2007). Standard errors double clustered by state-years of each pair are reported in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively. See Appendix 2 for descriptions of other variables.

	(1)	(2)	(3)	(4)
			High *Relationship-specific investment*	Low *Relationship-specific investment*
Ancestral Distance	-0.039**	-0.054**	-0.062**	-0.035
	(0.018)	(0.022)	(0.029)	(0.032)
Border	0.000	0.003	0.023	-0.016
	(0.015)	(0.018)	(0.028)	(0.024)
Geographic Distance	0.014***	0.021***	0.028***	0.016*
	(0.004)	(0.006)	(0.008)	(0.009)
Ind_diff	-0.025	-0.067***	-0.096***	-0.044
	(0.017)	(0.021)	(0.029)	(0.031)
Female_diff	-0.013	-0.021*	-0.043**	-0.005
	(0.010)	(0.012)	(0.017)	(0.016)
Age_diff	-0.003	-0.004	0.006	-0.013***
	(0.003)	(0.003)	(0.005)	(0.004)
College_diff	-0.003*	-0.004	-0.006*	-0.002
	(0.002)	(0.002)	(0.003)	(0.003)
Deal FE		Yes	Yes	Yes
Cluster by deal		Yes	Yes	Yes
Observations	5,188	5,188	2,744	2,434
Adjusted R-squared	0.004	0.044	0.032	0.062

Table 5. County-level ancestral distance and alliances

This table reports coefficient estimates and standard errors from regressions of count of alliances on *Ancestral Distance* between each county pair and control variables. Specifically, we estimate the following model using pooled regressions with county and state-pair fixed effects:

$$Count_{ij} = \alpha_0 + \beta_1 Ancestral\ Distance_{ij} + \beta_2 Same\ State_{ij}(Adjacent\ County_{ij}) + \beta_3 Geographic\ Distance_{ij}$$
$$+\beta_4 Ind\_Diff_{ij} + \beta_5 Female\_diff_{ij} + \beta_6 Age\_diff_{ij} + \beta_7 College\_diff_{ij} + \epsilon_{ij}$$

Standard errors double clustered by states of each pair are reported in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively. See Appendix 2 for descriptions of variables.

	(1)	(2)	(3)	(4)	(5)
Dependent	*count*	*count*	*count*	*count*	*count*
				count>0	*count*>0
Ancestral Distance	-0.003**	-0.002**	-0.006***	-1.880*	-2.518*
	(0.001)	(0.001)	(0.002)	(1.061)	(1.354)
Same State	0.004**				
	(0.002)				
Adjacent County		0.047***	0.042***	0.918	1.221
		(0.011)	(0.010)	(0.567)	(0.818)
Geographic Distance	0.002**	0.002*	0.007***	-0.002	1.115
	(0.001)	(0.001)	(0.003)	(0.224)	(0.833)
Ind_diff	-0.026***	-0.025***	-0.028***	-3.453**	-5.088**
	(0.006)	(0.006)	(0.006)	(1.583)	(2.019)
Female_diff	0.018	0.019	0.005	19.717***	22.050**
	(0.018)	(0.018)	(0.017)	(7.413)	(10.207)
Age_diff	0.000***	0.000***	0.000***	0.023	0.045
	(0.000)	(0.000)	(0.000)	(0.021)	(0.038)
College_diff	-0.222***	-0.222***	-0.214***	-6.244*	-5.677
	(0.056)	(0.056)	(0.053)	(3.349)	(3.971)
County FEs	Yes	Yes	Yes	Yes	Yes
State-pair FEs			Yes		Yes
Double cluster	Yes	Yes	Yes	Yes	Yes
Observations	4,912,543	4,912,543	4,912,543	4,073	3,805
Adjusted R-squared	0.030	0.030	0.035	0.226	0.177

Table 6. City-level ancestral distance and alliances

This table reports coefficient estimates and standard errors from regressions of count of alliances on *Ancestral Distance* between each city pair and control variables. The *Ancestral Distance* between a pair of cities is calculated as the "leave out" version of share shift induced by WWI and the Immigration Acts following Tabellini (2020). Specifically, we estimate the following model using pooled regressions with city and state-pair fixed effects:

$$Count_{ij} = \alpha_0 + \beta_1 Ancestral\ Distance\ (shift\text{–}share)_{ij} + \beta_2 Same\ State_{ij} + \epsilon_{ij}$$

Standard errors double clustered by cities of each pair are reported in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively. See Appendix 2 for descriptions of variables.

	(1)	(2)	(3)	(4)
Dependent	*count*	*count*	*count*	*count*
				count>0
Ancestral Distance (shift-share)	-2.076**	-1.952*	-1.980*	-64.823**
	(0.971)	(1.053)	(1.017)	(28.779)
Same State		0.034		
		(0.050)		
City FEs	Yes	Yes	Yes	Yes
State-pair FEs			Yes	Yes
Double cluster	Yes	Yes	Yes	Yes
Observations	16,108	16,108	15,892	229
Adjusted R-squared	0.141	0.141	0.117	0.216

Table 7. Announcement returns

This table reports coefficient estimates and standard errors from regressions of abnormal announcement returns on *Ancestral Distance* between each state pair and control variables. Specifically, we estimate the following model using pooled regressions:

$$CAR_{ij} = \alpha_0 + \beta_1 Ancestral\ distance_{ij} + \beta_2 Border_{ij} + \beta_3 Geographic\ Distance_{ij}$$
$$+\beta_4 Ind\_Diff_{ij} + \beta_5 Female\_diff_{ij} + \beta_6 Age\_diff_{ij} + \beta_7 College\_diff_{ij} + \epsilon_{ij}$$

The subsamples are both in-state and out-of-state deals (with *Ancestral Distance* set to 0 for in-state deals) in column (1), and only out-of-state deals in column (2). Standard errors double clustered by states of each pair are reported in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively. See Appendix 2 for descriptions of variables.

	(1)	(2)
Dependent	*CAR*	*CAR*
		Out of state deals
Ancestral Distance	-0.560**	-1.115**
	(0.260)	(0.517)
Border		-0.334
		(0.426)
Geographic Distance		0.079
		(0.111)
Ind_diff		0.024
		(0.197)
Female_diff		-0.088
		(0.234)
Age_diff		-0.260***
		(0.093)
College_diff		-0.000
		(0.062)
Double cluster	Yes	Yes
Observations	901	706
Adjusted R-squared	0.003	0.004

Table 8. Ancestral distance between inventors

This table reports coefficient estimates and standard errors from regressions of abnormal announcement returns on *Ancestral Distance_inventors* between partners and control variables. Specifically, we estimate the following model using pooled regressions:

$$CAR_{ij} = \alpha_0 + \beta_1 Ancestral\ Distance\_inventors_{ij} + \beta_2 Border_{ij} + \beta_3 Geograhic\ Distance_{ij}$$
$$+\beta_4 Ind\_Diff_{ij} + \beta_5 Female\_diff_{ij} + \beta_6 Age\_diff_{ij} + \beta_7 College\_diff_{ij} + \epsilon_{ij}$$

The subsamples are R&D-related deals in columns (1) and (2) and deals unrelated to R&D activities in column (3). Standard errors clustered by states of each pair are reported in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively. See Appendix 2 for descriptions of variables.

Dependent	(1) *CAR*	(2) *CAR*	(3) *CAR*
	R&D alliances		Non-R&D alliances
Ancestral Distance_inventors	-0.345*	-0.784**	0.471
	(0.184)	(0.393)	(0.331)
Border		0.019	
		(1.037)	
Geographic Distance		0.023	
		(0.122)	
Ind_diff		-0.053	
		(0.498)	
Female_diff		-0.418	
		(0.502)	
Age_diff		-0.534***	
		(0.115)	
College_diff		-0.147	
		(0.110)	
Double cluster	Yes	Yes	Yes
Observations	292	225	240
Adjusted R-squared	0.001	0.037	0.000

Table 9. Ancestral distance between corporate leaders

This table reports coefficient estimates and standard errors from regressions of abnormal announcement returns on *Ancestral Distance* between each state pair, connections between corporate leaders, and control variables. The connections between corporate leaders that we examine include *Same origin_CEO*, *Ancestral Distance_Board*, *Ties_CEO*, *Ties_Board*. The sample includes both in-state and out-of-state deals (with *Ancestral Distance* set to 0 for in-state deals) in Panel A, and only out-of-state deals in Panel B. Standard errors double clustered by states of each pair are reported in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively. See Appendix 2 for descriptions of variables.

Panel A. Stakeholder vs. leadership ancestral distance

	(1)	(2)	(3)	(4)	(5)
Dependent	*CAR*	*CAR*	*CAR*	*CAR*	*CAR*
					R&D alliances
Ancestral Distance	-0.545*	-0.530***	-0.540***	-0.530***	
	(0.307)	(0.038)	(0.078)	(0.102)	
Ancestral Distance_inventors					-0.704*
					(0.406)
Same Origin_CEO		0.554***	0.407**	0.323*	0.056
		(0.111)	(0.178)	(0.194)	(0.564)
Ancestral Distance_Board			0.041	-0.176	0.707
			(0.522)	(0.505)	(0.595)
Ties_CEO				-1.725**	-0.213
				(0.682)	(0.753)
Ties_Board				1.887	-2.489**
				(2.404)	(1.023)
Double cluster	Yes	Yes	Yes	Yes	Yes
Observations	719	719	641	627	203
Adjusted R-squared	0.002	0.005	0.001	0.014	0.001

Panel B. More controls

Dependent	(1) *CAR*	(2) *CAR*	(3) *CAR*	(4) *CAR*
Ancestral Distance	-1.239***		-1.711***	
	(0.409)		(0.618)	
Ancestral Distance_inventors		-1.095**		-1.784*
		(0.483)		(1.013)
Same Origin_CEO	0.333	-0.149	0.313	-0.418
	(0.237)	(0.454)	(0.338)	(0.424)
Ancestral Distance_Board	-0.745	-1.828	-1.078	-2.719
	(0.730)	(1.708)	(0.997)	(1.942)
Ties_CEO	-1.977**	-0.914**	-1.947**	-0.787
	(0.812)	(0.383)	(0.904)	(0.674)
Ties_Board	3.613	-1.887	3.708	-1.627
	(3.317)	(1.276)	(3.426)	(1.239)
Border	-0.857***	-0.635	-0.906***	-0.864
	(0.313)	(0.668)	(0.323)	(0.640)
Geographic Distance	-0.027	-0.082	-0.064	-0.156
	(0.076)	(0.219)	(0.084)	(0.216)
Ind_diff	-0.755***	-1.430	-0.678**	-1.378***
	(0.187)	(0.985)	(0.301)	(0.396)
Female_diff	-0.038	-0.670	0.009	-0.499
	(0.224)	(0.613)	(0.226)	(0.634)
Age_diff	-0.280**	-0.458**	-0.248*	-0.479**
	(0.110)	(0.189)	(0.126)	(0.196)
College_diff	-0.040	-0.142***	-0.013	-0.130
			(0.076)	(0.137)
ROA			1.758	-1.970
			(1.462)	(2.077)
ln(sales)			-0.195*	-0.357
			(0.103)	(0.282)
R&D			2.180	-6.056*
			(3.085)	(3.132)
Double cluster	Yes	Yes	Yes	Yes
Observations	488	160	482	160
Adjusted R-squared	0.016	0.032	0.018	0.041

Table 10. In-state and out-of-state ventures

This table reports coefficient estimates and standard errors from OLS regressions of locating the alliance within one of the partners' states on *Ancestral Distance* between each state pair and control variables. The dependent variable *Same State* is an indicator that equals one if the alliance is located within one of partners' state and zero otherwise. Standard errors double clustered by states of each pair are reported in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively. See Appendix 2 for descriptions of other variables.

Dependent	*Same State (partner and new venture)*	
	(1)	(2)
Ancestral Distance	-0.084***	-0.079***
	(0.023)	(0.023)
Border	0.022	0.001
	(0.018)	(0.024)
Geographic Distance	0.031***	-0.010
	(0.007)	(0.007)
Ind_diff	-0.033	0.018
	(0.022)	(0.053)
Female_diff	-3.463***	0.443
	(0.974)	(1.836)
Age_diff	-0.004**	-0.006
	(0.002)	(0.008)
College_diff	-0.521**	-0.678*
	(0.261)	(0.348)
State FEs		Yes
Double cluster	Yes	Yes
Observations	8,434	8,434
Adjusted R-squared	0.168	0.187

Table 11. New venture location

This table reports coefficient estimates and standard errors from OLS regressions of actual alliance location on *Ancestral Distance* between each state pair and control variables, including various fixed effects. For each deal, we create 50 counterfactuals of the remaining 50 states (including D. C.) that are not the actual location of the alliance. The dependent variable *Actual location* is an indicator that equals one for the actual location and zero otherwise. The average values (e.g., Avg. Ancestral Distance) are the average values (e.g., ancestral distance) between the partners and the (actual or counterfactual) alliance location. Standard errors double clustered by states of each pair are reported in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively. See Appendix 2 for descriptions of other variables.

Dependent		*Actual location*	
	(1)	(2)	(3)
Avg. Ancestral Distance	-0.041**	-0.032**	-0.055**
	(0.017)	(0.013)	(0.023)
Avg. Border	0.004	0.008**	0.003
	(0.005)	(0.004)	(0.007)
Avg. Geographic Distance	0.005	0.003	0.007
	(0.003)	(0.002)	(0.005)
Avg. Ind_diff	-0.022***	-0.019***	-0.022***
	(0.006)	(0.005)	(0.006)
Avg. Female_diff	-0.050	0.167	-0.272
	(0.216)	(0.285)	(0.232)
Avg. Age_diff	-0.215**	-0.219***	-0.324***
	(0.107)	(0.075)	(0.120)
Avg. College_diff	-0.002*	-0.001	-0.003
	(0.001)	(0.001)	(0.002)
Year FEs	Yes	Yes	Yes
State FEs		Yes	
Deal FEs			Yes
Double cluster	Yes	Yes	Yes
Observations	126,447	126,446	126,447
Adjusted R-squared	0.008	0.060	-0.010

Appendix 1: 1980 Census ancestry group

Panel A lists all 138 categories of single ancestry group or unique three-origin multiple ancestry group and Panel B lists the 10 broader ancestry groups on the 1980 U.S. Census.

Panel A: 138 categories of single ancestry group or unique three-origin multiple ancestry group

	Ancestry group		Ancestry group
1	Austrian	45	Belorussian
2	Basque	46	Slavic
3	Belgian	47	Gypsy
4	Cypriot	48	Other Eastern European
5	Danish	49	Central European
6	Dutch	50	Spanish categories: Central and South American
7	English	51	Spanish categories: Other Spanish
8	Welsh	52	Haitian
9	Scottish	53	Jamaican
10	Northern Ireland	54	U.S. Virgin Islander
11	Finnish	55	Trinidaian and Tobagonan
12	French	56	Bahamian
13	German	57	French West Indian
14	Greek	58	Guyanese
15	Irish	59	Other Caribbean, Central and South American
16	Italian	60	Brazilian
17	Norweigian	61	Egyptian
18	Portuguese: Azorean	62	Moroccan
19	Portuguese: Madeiran	63	Algerian, Libyan, Tunisian, Moor, Alhucemas, Sudanese
20	Portuguese: Portuguese	64	Other North African
21	Swedish	65	Iraqi
22	Swiss	66	Jordanian
23	Scandinavian	67	Lebanese
24	European	68	Saudi Arabian
25	Other Western European	69	Syrian
26	Other Northern European	70	Palestinian
27	Other Southern European	71	Arabian
28	Albanian	72	Other Southwest Asian
29	Czechoslovakian	73	Iranian
30	Slovak	74	Israeli
31	Hungarian	75	Turkish
32	Latvian	76	Assyrian
33	Lithuanian	77	Kurd
34	Polish	78	Central African
35	Rumanian	79	Cape Verdean
36	Croatian	80	Ghanian
37	Serbian	81	Liberian
38	Slovene	82	Nigerian
39	Yugoslavian	83	Mauratanian
40	Russian	84	Other West African
41	Armenian	85	South African
42	Georgian	86	Other South African
43	Ruthenian	87	Ethiopian
44	Ukrainian	88	Kenyan

	Ancestry group		Ancestry group
89	Tanzanian	114	Part-Hawaiian
			Fijian, New Guinean, American Samoan,
			Tokleau Islander, Guamanian, Chamarro,
			Marshallese, Carolinian, Melanesan,
			Micronesian, Polynesian, Pacific Islander,
90	Ugandian	115	Samoan
91	Djibouti, Somalian	116	Other Pacific
92	Other East African	117	Afro-American
93	African	118	Canadian
94	All other Subsaharan African	119	French Canadian
95	Chinese	120	Other North American
96	Taiwanese	121	American Indian-Eskimo-Aleut
97	Filipino	122	American Indian-English-French
98	Japanese	123	American Indian-English-German
99	Korean	124	American Indian-English-Irish
100	Vietnamese	125	American Indian-German-Irish
101	Asian Indian	126	Dutch-French-Irish
102	Pakistani	127	Dutch-German-Irish
103	Cambodian	128	Dutch-Irish-Scotch (or Scottish)
104	Indonesian	129	English-French-German
105	Laotian	130	English-French-Irish
106	Thai	131	English-German-Irish
107	Indo-Chinese	132	English-German-Swedish
	Ceylonese, Burmese, Okinawan,		
108	Malyasian, Eurasian, Asian	133	English-Irish-Scotch
109	Afghan	134	English-Scotch-Welsh
110	All other Asian	135	French-German-Irish
111	Australian	136	German-Irish-Italian
112	New Zealander	137	German-Irish-Scotch
113	Hawaiian	138	German-Irish-Swedish

Panel B: 10 categories of broader ancestry group

	Broader ancestry group
1	Western, Northern, and Southern Europe
2	Eastern and Central Europe
3	Spanish categories
4	Non-Spanish Caribbean, Central and South American
5	North Africa
6	Southwest Asia
7	Subsaharan Africa
8	Other Asia
9	Pacific
10	North America (except Spanish categories)

Appendix 2. Variable definitions

Variables	Descriptions
State-pair variables:	
Count	The number of alliances between the state pairs over the sample period.
ln(count)	The natural logarithm of *Count*.
Ancestral Distance	For each state, we calculate the fraction of people who reported a specific ancestry group out of the population for all 138 ancestry group categories listed on the 1980 Census (see Appendix 1). We then calculate ancestral distance between two states as the Manhattan (L1) distance between their ancestral vectors (with 138 dimensions): $Ancestral\ Distance_{x,y} = \sum_{i=1}^{138} \lvert x_i - y_i \rvert$
Border	An indicator that equals one if the paired states border each other, and zero otherwise.
Geographic Distance	The geographic distance between the paired states measured in miles.
Ind_diff	The absolute 1-norm distance between the paired states' vectors of market value weighted fraction for firms in each 2-digit SIC.
Female_diff	The absolute difference between the paired states' fractions of females in the state's population.
Age_diff	The absolute difference between the paired states' median ages of the state's population.
College_diff	The absolute difference between the paired states' fractions of people 25 years old or older who obtained at least a bachelor's degree.
Polit_distance	The Manhattan distance between voting vectors of each pair of states averaged using data from the four presidential elections during our sample period (2004, 2008, 2012, 2016). The voting vectors are vectors of fractions of votes for Democratic, Republican, and Independent (or Other) candidates in each state.
Relig_distance	The Manhattan distance between vectors of rate of adherence to top ten religions of each pair of states based on data from the 2010 Religious Congregations and Membership Study.
HHI_diff	The absolute difference between the paired states' Herfindahl–Hirschman Index of ancestral composition, calculated as the sum of squares of each ancestry group's share in the state's population.
Tax_diff	The absolute difference between the average state-corporate-tax rates over 2004–2017 of the paired states.
County-level variables:	
ΔRepublican share	The change in a county's Republican voting shares in a presidential election from the last election.
ΔSinclair	The change in *Sinclair*, where *Sinclair* is an indicator that equals one if the county has Sinclair and zero otherwise
ΔAC weighted Sinclair$_i$	The change in *Ancestral connection (AC) weighted Sinclair* of county i in an election year from the last election, with *AC weighted Sinclair* being calculated as $\sum_j Ancestral\ connection_{ij} Sinclair_j \,/\, \sum_j Ancestral\ connection_{ij}$, where *Ancestral connection$_{ij}$* is the ancestral connection between county i and j calculated as (2-*Ancestral distance$_{ij}$*).

ΔGeo. weighted Sinclair$_i$	The change in *geographic proximity (Geo.) weighted Sinclair* of county i in an election year from the last election year, with *Geo. Weighted Sinclair* being calculated as $\sum_j Proximity_{ij} Sinclair_j \,/\, \sum_j Proximity_{ij}$, where $Proximity_{ij}$ is the geographic proximity between county i and j calculated as the inverse of the geographic distance between county i and j.
ΔFB weighted Sinclair$_i$	The change in *Facebook connection (FB) weighted Sinclair* of county I in an election year from the last election year, with *FB weighted Sinclair* being calculated as $\sum_j FB_{ij} Sinclair_j \,/\, \sum_j FB_{ij}$, where FB_{ij} is the Facebook connection between county i and j calculated as the number of Facebook connection between county i and j in 2018 and rescaled to have a minimum value of 1, and a maximum value of 1,000,000.
Deal-level variables:	
Same state	An indicator variable that equals one if the alliance partners are from the same state, and zero otherwise.
Ancestral Distance	The *Ancestral Distance* between the states where the alliance partners reside.
Border	An indicator that equals one if the states where the alliance partners reside border each other, and zero otherwise.
Geographic Distance	The geographic distance in miles between the states where the alliance partners reside.
Ind_diff	The absolute 1-norm distance between the partner states' vectors of market-value weighted fraction for firms in each 2-digit SIC.
Female_diff	The absolute difference between the fractions of females in the partner states' population.
Age_diff	The absolute difference between the median ages of the partner states' population.
College_diff	The absolute difference between the fractions of people 25 years old or older who obtained at least a bachelor's degree in the partner states' population.
Relationship-specific Investment	The weighted average importance of relationship-specific investment across inputs for a given industry following Nunn (2007). The weights are the proportions of intermediate inputs used in the production of final good for each industry from 2012 United States I-O Use Table. We follow Rauch (1999) to identify the degree of relationship-specific investments required for each input.
CAR	The 3-day cumulative abnormal stock return over the window [-1, 1] where day zero is the announcement date of the alliance. Abnormal returns are calculated from a Fama-French three factor model estimated over 100 trading days ended 20 trading days prior to the announcement date.
Ancestral Distance_inventors	The *Ancestral Distance* measured using the partners' ancestral vectors of their patent inventors.
Same origin_CEO	An indicator that equals one if the CEOs of partners are from the same ancestry group.
Ties_CEO	The number of ties (professional, education, other activities) between partners' CEOs following Fracassi and Tate (2011).
Ancestral Distance_Board	The *Ancestral Distance* measured using the boards' ancestral vectors.

Ties_Board	The number of ties (professional, education, other activities) between partners' boards (*Ties_Board*) following Fracassi and Tate (2011).
ROA	The total assets weighted average *ROA* of partners, where *ROA* is net income divided by assets
ln(sales)	The natural logarithm of average total sales of partners
R&D	The average R&D expenditure divided by total assets of partners

Appendix 3. Robustness tests

This table reports coefficient estimates and standard errors from regressions of the number of alliances on *Ancestral Distance* between each state pair and control variables. Column (1) excluding states DE, DC, HI, SD and ND. Column (2) includes additional control variables *HHI_diff* and *Tax_diff*. In column (3), *Ancestral Distance* is based on the 10 broader ancestry group categories of the 1980 Census in Appendix 1. In column (4), *Ancestral Distance* is based on 2010 Census data. In column (5), *Ancestral distance* is measured as L2 distance between ancestral vectors. State fixed effects are included. Standard errors double clustered by states of each pair are reported in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively. See Appendix 2 for descriptions of variables.

	(1)	(2)	(3)	(4)	(5)
Dependent	*ln(count)*	*ln(count)*	*ln(count)*	*ln(count)*	*ln(count)*
Ancestral Distance	-0.468***	-0.303***			
	(0.136)	(0.103)			
Ancestral Distance$_{10}$			-0.528***		
			(0.143)		
Ancestral Distance$_{2010}$				-0.445***	
				(0.157)	
Ancestral Distance$_{L2}$					-0.416*
					(0.263)
Border	0.136***	0.150***	0.174***	0.162***	0.239***
	(0.043)	(0.042)	(0.044)	(0.044)	(0.042)
Geographic Distance	-0.033	-0.015	-0.023	-0.006	-0.032
	(0.021)	(0.030)	(0.027)	(0.026)	(0.031)
Ind_diff	-0.881***	-0.857***	-0.854***	-0.868***	-0.557**
	(0.156)	(0.142)	(0.138)	(0.138)	(0.242)
Female_diff		-0.058	-0.055	-11.233**	-6.407
		(0.040)	(0.040)	(5.096)	(4.758)
Age_diff		-0.060**	-0.066**	0.017**	-0.074**
		(0.027)	(0.027)	(0.007)	(0.031)
College_diff		-0.026*	-0.030**	-2.690***	-2.929*
		(0.014)	(0.015)	(0.875)	(1.556)
HHI_diff		-0.621			
		(0.586)			
Tax_diff		0.004			
		(0.006)			
State FEs	Yes	Yes	Yes	Yes	Yes
Double cluster	Yes	Yes	Yes	Yes	Yes
Observations	1,013	1,246	1,246	1,246	1,246
Adjusted R-squared	0.814	0.803	0.805	0.805	0.786

Appendix 4. Propensity of forming alliance—entropy balanced sample

This table reports coefficient estimates and standard errors from OLS regressions of actual alliance partners on *Ancestral Distance* between partners' states and control variables using a match sample with entropy balancing. The dependent variable is an indicator that equals one if the partners are the actual partners of a deal and zero otherwise. For any given firm in the alliance sample, we form counterfactual deals by selecting counterfactual partners that have not formed alliances within the three-year window centered around the year of the deal, are from the same four-digit SIC industry but different state as the actual partner of the focal firm, and have a firm size within 50% to 150% of the actual partner of the focal firm. The sample is re-weighted using entropy balancing to balance the absolute differences in each partner pair's characteristics, including capital expenditure, R&D, return of assets, cash holding, Tobin's Q, financial leverage, total assets, and sales growth, between the actual and counter partners. The sample includes all deals with partners from different states. Standard errors double clustered by actual deals are reported in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively. # indicates statistical significance at the 10% level (one-sided). See Appendix 2 for descriptions of other variables.

	(1)	(2)
Ancestral Distance	-0.130**	-0.140#
	(0.060)	(0.086)
Border	0.006	-0.002
	(0.050)	(0.073)
Geographic Distance	0.043***	0.065***
	(0.014)	(0.023)
Ind_diff	-0.134**	-0.245***
	(0.055)	(0.085)
Female_diff	-0.032	-0.067
	(0.031)	(0.050)
Age_diff	-0.010	-0.015
	(0.010)	(0.015)
College_diff	-0.008	-0.013
	(0.007)	(0.010)
Deal FE		Yes
Cluster by deal		Yes
Observations	4,061	4,061
Adjusted R-squared	0.019	0.120

Appendix 5. Alternative measures of announcement returns

This table reports coefficient estimates and standard errors from regressions of abnormal announcement returns on *Ancestral Distance* between each county pair and control variables. Specifically, we estimate the following model using pooled regressions:

$$CAR_{ij} = \alpha_0 + \beta_1 Ancestral\ distance_{ij} + \beta_2 Border_{ij} + \beta_3 Distance_{ij}$$
$$+\beta_4 Ind\_Diff_{ij} + \beta_5 Female\_diff_{ij} + \beta_6 Age\_diff_{ij} + \beta_7 College\_diff_{ij} + \epsilon_{ij}$$

CAR is measured as market adjusted returns over [-1. 1] in column (1), abnormal returns over [-1, 1] estimated with a market model in column (2), and abnormal returns over [-2, 2] estimated with the Fama-French three-factor model in column (3). *Border* is an indicator that equals one if the counties of the partners are adjacent, and zero otherwise. Standard errors double clustered by counties of each pair are reported in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively. See Appendix 2 for descriptions of variables.

	(1)	(2)	(3)
Dependent	$CAR3_{market\ adj.}$	$CAR3_{market\ model}$	$CAR5_{Fama\text{-}French}$
Ancestral Distance	-0.922**	-1.089**	-1.014***
	(0.415)	(0.497)	(0.346)
Border	-0.244	-0.389	-0.654
	(0.432)	(0.456)	(0.467)
Geographic Distance	0.077	0.053	0.067
	(0.098)	(0.102)	(0.132)
Ind_diff	-0.028	-0.014	0.593
	(0.244)	(0.200)	(0.418)
Female_diff	-0.189	-0.174	0.164
	(0.249)	(0.283)	(0.321)
Age_diff	-0.235***	-0.258***	-0.272***
	(0.075)	(0.099)	(0.094)
College_diff	-0.031	-0.022	-0.083
	(0.075)	(0.062)	(0.096)
Double cluster	Yes	Yes	Yes
Observations	706	706	706
Adjusted R-squared	0.004	0.006	0.002

Appendix 6. County-level ancestral distance and announcement returns

This table reports coefficient estimates and standard errors from regressions of abnormal announcement returns on *Ancestral Distance* between each county pair and control variables. Specifically, we estimate the following model using pooled regressions:

$$CAR_{ij} = \alpha_0 + \beta_1 Ancestral\ distance_{ij} + \beta_2 Border_{ij} + \beta_3 Distance_{ij}$$
$$+\beta_4 Ind\_Diff_{ij} + \beta_5 Female\_diff_{ij} + \beta_6 Age\_diff_{ij} + \beta_7 College\_diff_{ij} + \epsilon_{ij}$$

Border is an indicator that equals one if the counties of the partners are adjacent, and zero otherwise. Standard errors double clustered by counties of each pair are reported in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively. See Appendix 2 for descriptions of variables.

	(1)
Dependent	*CAR*
Ancestral Distance	-0.888*
	(0.490)
Border	-0.297
	(0.473)
Geographic Distance	-0.019
	(0.220)
Ind_diff	-0.067
	(1.025)
Female_diff	0.046
	(0.130)
Age_diff	-0.039
	(0.061)
College_diff	0.014
	(0.026)
Double cluster	Yes
Observations	783
Adjusted R-squared	0.002

Appendix 7. Changes in operating performance

This table reports coefficient estimates and standard errors from regressions of changes in operating performance on *Ancestral Distance* between each county pair and control variables. Specifically, we estimate the following model using pooled regressions:

$$\Delta ROA_{ij} = \alpha_0 + \beta_1 Ancestral\ distance_{ij} + \beta_2 Border_{ij} + \beta_3 Distance_{ij}$$
$$+\beta_4 Ind\_Diff_{ij} + \beta_5 Female\_diff_{ij} + \beta_6 Age\_diff_{ij} + \beta_7 College\_diff_{ij} + \epsilon_{ij}$$

ΔROA is the change in weighted average performance of partners from year t-1 to t, where year t is the year of the deal and weighted average performance is the total assets weighted return on assets (*ROA*). The subsamples are all deals in column (1) and out-of-state deals in column (2). Standard errors double clustered by counties of each pair are reported in parentheses. The asterisks *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-sided), respectively. See Appendix 2 for descriptions of variables.

	(1)	(2)
Dependent	ΔROA	ΔROA
		Out of state
Ancestral Distance	-0.007**	-0.008*
	(0.003)	(0.005)
Border		0.044
		(0.029)
Geographic Distance		0.067***
		(0.022)
Ind_diff		-0.081**
		(0.036)
Female_diff		-0.046*
		(0.023)
Age_diff		0.009
		(0.007)
College_diff		0.010
		(0.006)
Double cluster	Yes	Yes
Observations	845	640
Adjusted R-squared	0.001	0.002