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Ancestral connections and corporate alliances☆

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ABSTRACT

This paper studies how culture works as an implicit incentive alignment mechanism in corporate alliances. We measure the ancestral connection between different corporate headquarters places, using historical immigration from different countries to different areas of the U. S. When forming business alliances, the ancestral composition of the area where firms locate plays an important role in their choices of partners and the location of new ventures. Exploiting immigration to 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 historical immigrant inflows is associated with an increase in alliance intensity today. Finally, partnering firms 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.

1. Introduction

Extant literature on family businesses emphasizes the vital role of "family assets" in their success, which include intangible assets such as personal values and beliefs, connections, reputation etc., that could reduce transaction costs with various stakeholders (Bennedsen and Fan, 2014; Bennedsen et al., 2015; Fan et al., 2022). Anecdotally, immigrants often bring their cultural values and connections, as well as facilitate business and trades between home and host countries (Bae, 2017; Cohen et al., 2017). Recognizing the influence of shared cultural heritage, this paper studies whether there is systematic evidence for the importance of ancestral networks in the U.S. corporate sector today. We focus on firms' decisions to form alliances—an important corporate decision that changes firm boundaries, and one that also often requires a decision to determine the location of the new venture.

Recent theoretical literature has suggested that culture can shape firm boundaries, because, at times, implicit norms are more

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efficient than detailed contracts (Gorton and Zentefis, 2020).[1] In fact, announcements of alliance formation often emphasize the role of cultural fit.[2] In light of the emerging literature emphasizing historical immigration as a seed of people's values and preferences that evolve slowly over time (e.g., Guiso et al., 2006; Spolaore and Wacziarg, 2013; Giuliano and Tabellini, 2020; Sequeira et al., 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, similar to the role of intangible family assets in family firms. Different measures of corporate culture in the literature capture varying specific aspects of shared values and beliefs[3]; with ancestral background, we take a more holistic approach and aim to measure the deep root of culture. 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.

Alliances 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 decisions given the possibility of hold-up problems, and more generally, the importance of cooperation between partners (Robinson and Stuart, 2007). 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 both the organizational and geographic firm boundaries.

We retrieve information on alliance deals announced between 2004 and 2017 from Securities Data Company (SDC) Platinum. Prior research suggests that prevailing culture in the areas where firms reside, for example local religiosity, affects corporate decisions and outcomes.[4] Focusing on a deep cultural root—the ancestral composition of the local population (Guiso et al., 2006)—we first conduct state-pair-level analysis of alliance activities by examining the intensity of alliances formed by partners with headquarters in the 1275 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 0.032 increase of (scaled) alliance intensity, similar to the increase in alliance intensity (0.048) 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 those between firms with greater vertical relatedness (Frésard et al., 2020), which are more subject to the hold-up problem.

The identification relies on the extent to which ancestral connection is determined by *historical* immigration patterns and thus not driven by *current* economic conditions. To capture a supply-push component of historical immigration, we exploit exogenous variation in immigration to U.S. cities, induced by WWI and the 1921 and 1924 Immigration Acts, using a two-stage least squares (2SLS) approach. These shocks altered migration flows to the U.S. from different sending regions to different degrees and thus unexpectedly altered the number and the mix of immigrants in U.S. cities. Following Tabellini (2020), we construct an instrument based on historical immigration shocks by apportioning flows from each sending region to a city net of the individuals who eventually settle in that city. We find that a decrease in instrumented ancestral distance between two cities is significantly associated with an increase of (scaled) alliance intensity, after controlling for city and state-pair fixed effects.

For a small subset of deals with only public partners, we find that ancestral distance, a proxy for cultural fit between partners, correlates significantly and negatively with abnormal returns around alliance announcements, whereas geographic distance does not have a significant effect.[5] One possibility is that lower ancestral distance facilitates coordination and cooperation between employees of partners when operating the new alliance, which reduces hold-up and generates more synergy. Other possible, non-exclusive channels include stockholders—many of whom are local (e.g., Coval and Moskowitz, 1999) and thus welcome alliances formed between partners with low ancestral distance, either due to lower information friction or innate preferences (e.g., Ayers et al., 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 Xuan, 2014). Our study highlights the importance of ancestral connection in reducing frictions between stakeholders. Ancestral connection could play an important role to facilitate knowledge transfer in alliances, which might be subject to hold-up given the "sunk cost" nature of knowledge transfer. Prior literature on knowledge transfer focuses on the importance of geographic proximity (Jaffe et al., 1993; Saxenian, 1990), but Rosenkopf and Almeida (2003) point out that the formation of alliance increases knowledge transfer across regional boundaries. 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, similar to the role of intangible family assets in the family firms.

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. 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

[1] 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).

[2] 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/.

[3] See Gorton et al. (2021) for a literature review on corporate culture, and Aggarwal et al. (2016) for a review on culture and finance.

[4] See, e.g., Hilary and Hui (2009), Adhikari and Agrawal (2016), McGuire et al. (2012), and Jiang et al. (2018).

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

are only suggestive due to the limited sample size of this analysis, they hint at a distinctive channel of influence arising from ancestral connection between non-executive employees or 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, partners with larger ancestral distances between them are significantly less likely to place the new venture in the same state as a partner, controlling for partnering states' fixed effects. 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 the average ancestral distance from partners' locations and 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.

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 positive and negative effects of ethnic diversity on economic outcomes.[6] Pan et al. (2017) infer corporate risk culture using corporate officers' ancestral background and study its effect on corporate risk taking. We 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. Our paper thus answers the call in Fan et al. (2022) for future research on the role of culture in governing stakeholder relationships, after finding evidence of cultures and norms shaping the governance structures and contractual relationships in family firms.

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 et al. (2017) study the effect of cultural proximity between borrowers and lenders on loan outcomes. Cohen et al. (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 mitigates partnering frictions when forming alliances.

2. Hypothesis development

Corporate alliances, such as strategic alliances and joint ventures, are an important organizational form through which firms grow into new product markets or geographic territories, thus expanding firm boundaries. Theoretically, alliances are often modeled as prisoner's dilemma (e.g., Gulati et al., 1994), where successful outcomes rely on both partners cooperating to reach the joint goal of value creation (i.e., choosing the payoff dominant strategy). Shared values and beliefs originated from ancestral connection could work as an implicit incentive alignment mechanism when partners face unforeseeable contingencies or multiple equilibria (Hermalin, 2001), which mitigates hold-up and encourages relationship-specific investments.[7]

Consider a general version of the hold-up problem where agents make relationship-specific investments, and then need to agree on some collective action (e.g., Rogerson, 1992). The choice of collective action resembles a problem of choosing public goods for the alliance partners, such as the type of shared knowledge to produce in an alliance or the right course when facing unexpected product market shocks. The production of such public goods usually requires some "sunk cost" such as knowledge transfer (*ex ante*), which is subject to hold-up. As Spolaore and Wacziarg (2019) show, when the conflict is about determining the type of such public goods (ex post), the probability of conflict is lower when the two parties are more closely related in their ethnic origins, due to shared norms and values. While relying on culture (implicit norms) to coordinate decisions entails both potential benefits and costs (e.g., the cost to acquire the knowledge of common "codes" as in Crémer (1993) and the costs due to groupthink and less information collection as in Van den Steen (2010)), in the specific context of producing public goods in corporate alliances (Agarwal et al., 2010), we hypothesize that:

H1. Stronger ancestral connections between firms are associated with a higher tendency for firms to form alliances.

More generally, the bonding arising from shared norms and values could encourage communication and cooperation (Fan et al., 2022). Therefore, ancestral connection may enhance information sharing (Fisman et al., 2017) and facilitate collaboration (Tabellini, 2008) between partners, both critical for successful alliances (Das and Teng, 1998; Nicolaou et al., 2011). Conditional on firms forming an alliance, better information sharing and collaboration between ancestrally connected firms would likely generate more synergies, e.g., through collaborative training that leads to knowledge transfer. A good analogy is the role of founding-family engagement and the role of cultural factors in family firms (e.g., Fan et al., 2022), and more broadly how intangible family assets facilitate collaboration (Bennedsen and Fan, 2014). Other potential channels for synergy include shared customer base, common ownership, or other firm characteristics that could be (pre-)determined by ancestral connections between firms. Overall, we argue that ancestral connections can facilitate alliance formation for two non-exclusive reasons—mitigating potential hold-up problems and increasing synergy through collaboration and information sharing.

[6] 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.

[7] In corporate alliances, hold-up may arise with incomplete contracting, for example due to unforeseeable contingencies. When unexpected outcomes occur, the partners could withhold cooperation ex post (Hart, 2009), which reduces ex ante relationship-specific investments.

Based on the above arguments, we hypothesize that in addition to H1:

H2. Conditional on the decision to form an alliance, stronger ancestral connections between the partners are associated with better alliance performance.

Another important alliance decision is where to locate the new venture. We hypothesize that the new venture is more likely to be placed in neither partner's state, if partners are concerned about potential problems (e.g., disagreement on the collective action) and thus reluctant to give the other party proximity advantage to the new venture. This could be the case when the ancestral distance between the partners is larger. For new ventures outside of both partners' states, a cultural "middle-ground" is likely the bargaining outcome for the venture location.

H3. Stronger ancestral connections between firms are associated with a higher tendency for firms to locate the new venture in one of the partners' state.

H4. For new ventures located outside of partners' states, they are more likely to be placed in a state with stronger average ancestral connection with both partners.

3. Data and sample

3.1. 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.[8] 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 $(x_1, x_2, \ldots, x_{138})$ for each place x and calculate *Ancestral Distance* between two places *x* and *y*, as the Manhattan distance between their ancestral vectors[9]:

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

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 Fig. 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. Fig. 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 4.1, 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 et al., 2021; Hong and Kostovetsky, 2012; Cookson et al., 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. Martin and McCrain (2019) and Levendusky (2022) document that these acquisitions were not driven by local economic conditions or demographic characteristics, but led to a significant rightward shift in the ideological slant of coverage, thus a rightward shift in local political attitudes. To examine the effect of ancestral connection in propagating this ideological shock, 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 3104 counties and 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

[8] https://www.census.gov/acs/www/about/why-we-ask-each-question/ancestry/

[9] Our results are robust to using the Euclidean (L_2) distance as discussed in section 4.1.

Table 1
. Descriptive Statistics

	Obs.	Mean	Median	Std. Dev.	Min	Max
State-pair variables:						
Number of Alliances	1275	7.32	1.00	24.96	0.00	495
Alliances Intensity	1275	0.16	0.08	0.25	0.00	2.49
Ancestral Distance	1275	0.91	0.91	0.32	0.08	1.66
Largest Overlap	1246	0.18	0.16	0.08	0.04	0.50
Border	1246	0.09	0.00	0.28	0.00	1.00
Geographic Distance	1246	1.95	1.60	1.44	0.04	8.24
Ind_diff	1246	1.68	1.73	0.23	0.81	2.00
Female_diff	1246	1.10	0.76	1.04	0.00	6.74
Age_diff	1246	1.82	1.40	1.56	0.00	10.50
College_diff	1246	3.73	3.14	2.90	0.00	17.04
Deal-level variables:						
Same state (partner and new venture)	8434	0.72	1.00	0.45	0.00	1.00
Ancestral Distance	8434	0.78	0.78	0.25	0.08	1.60
Border	8434	0.12	0.00	0.33	0.00	1.00
Geographic Distance	8434	2.06	1.72	1.33	0.04	8.19
Ind_diff	8434	1.43	1.45	0.26	0.66	2.00
Female_diff	8434	0.01	0.01	0.01	0.00	0.06
Age_diff	8434	1.78	1.60	1.52	0.00	10.50
College_diff	8434	0.03	0.03	0.02	0.00	0.17
CAR	901	0.35%	0.26%	3.48%	−17.78%	23.32%
CapEx_diff	4616	0.03	0.02	0.05	0.00	0.24
RD_diff	4616	0.11	0.06	0.15	0.00	0.68
ROA_diff	4616	0.22	0.1	0.29	0.00	1.41
Cash_diff	4616	0.25	0.17	0.23	0.00	0.87
TobinQ_diff	4616	1.49	0.87	1.72	0.01	8.66
Assets_diff	4616	2.79	2.24	2.15	0.04	7.84
SalesGrowth_diff	4616	0.54	0.22	0.98	0.00	5.37
Leverage_diff	4616	0.21	0.15	0.22	0.00	1.02
Patent Similarity	4616	0.14	0.00	0.30	0.00	1.00

This table reports descriptive statistics for the variables used in our main analyses. See Section 3.2 for the sample description, and Appendix 2 for a detailed description of the variables.

whether Sinclair entered the local media market or media markets in connected counties.[10]

Appendix 3 reports the results. First, entries of Sinclair to ancestrally connected counties have a significant and positive effect on the change in Republican voting share. The result holds after controlling for local Sinclair entry. 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. Fisman et al. (2017) suggest that social connections are endogenously formed as a consequence of common cultural endowments. While we aim to capture the deep root of persistent cultural connection through ancestral connections, social ties and connections are often outcomes of individual choices as well. Finally, our results are robust to using county and year fixed effects instead. 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.

3.2. *Alliance 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, 8434 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.

[10] 7.2% of the county-years in our sample had Sinclair entry, while exit was rare (only 0.7%).

[11] Announcement abnormal returns of deals are calculated as the market value weighted announcement abnormal returns to both partners as discussed in section 5.1. 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.

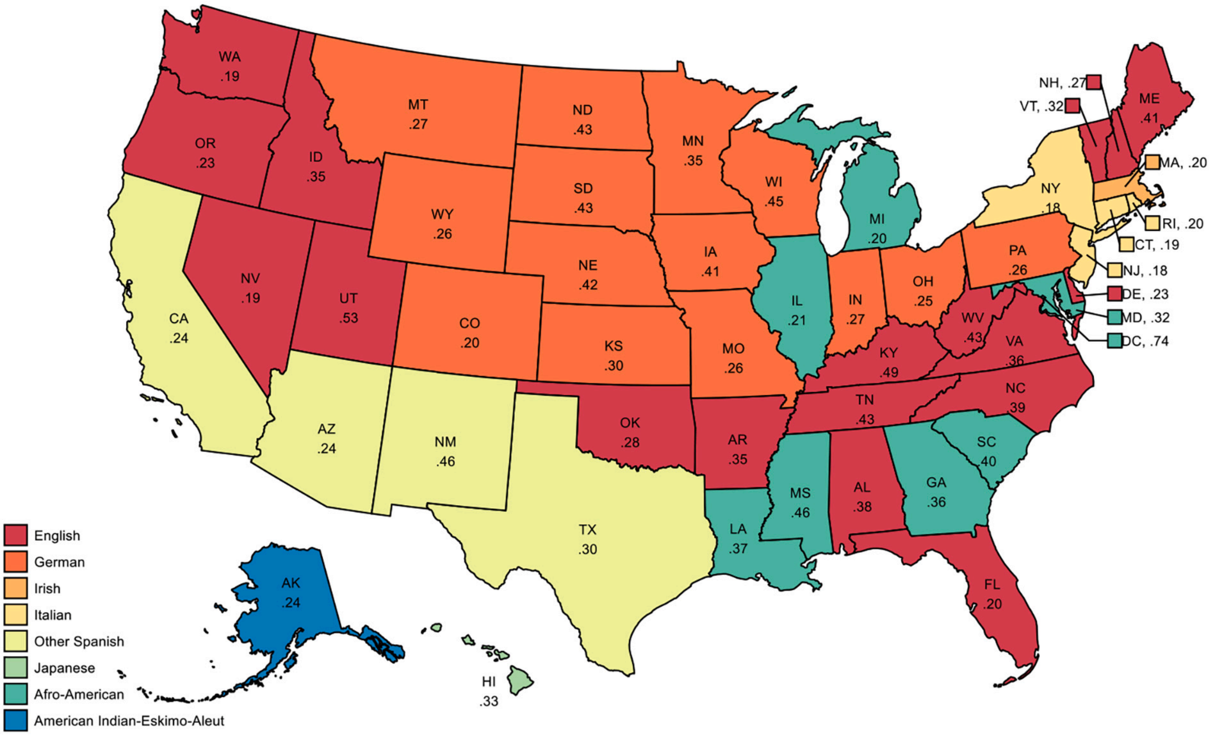

Fig. 1. Most common ancestry group.
This figure plots the most common ancestry group of each state and the D.C. of U.S. The numbers are the fraction of the state's population represented by the most common ancestry group within the state.

3.3. Other variables

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 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.

[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

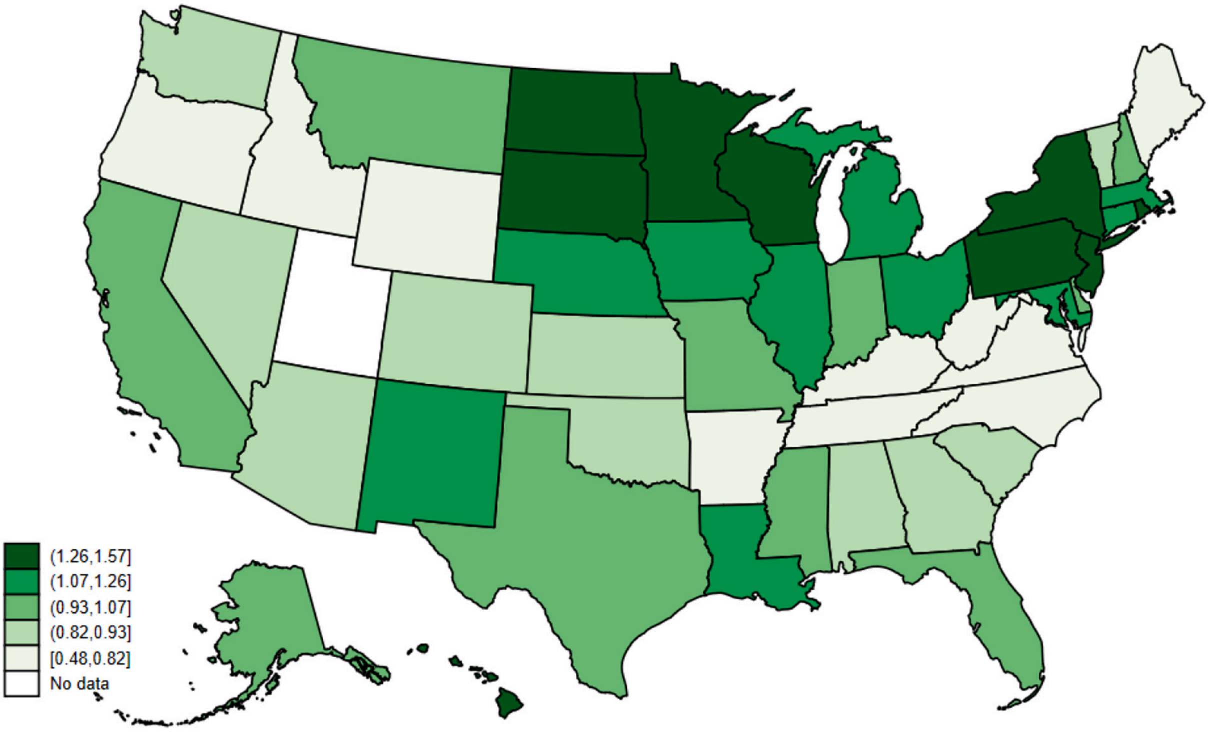

Fig. 2. Ancestral distance to Utah.
This figure graphs the *Ancestral Distance* between Utah and other states and the D.C. of U.S. Darker green represents a larger ancestral distance. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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 et al. (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.

To capture firm level determinants of alliance formation, we collect data from Computat to calculate firm-level characteristics (e.g., capital expenditure, R&D, return on asset, cash holding, Tobin's Q, financial leverage, total assets, and sales growth), and calculate the absolute differences in these characteristics between a pair of firms. We also calculate *Patent Similarity* to capture the similarity in innovation activities between a pair of firms following Li et al. (2019). We use the extended data on patent applications and classes following Kogan et al. (2017). For each year t, we calculate the fraction of patent with application years from t-2 to t in each patent class to form a vector of patent output. *Patent Similarity* is the cosine similarity between the patent outputs of a pair of firms.

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 (2012), 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.

Table 1 reports the descriptive statistics of the main variables. The average number of alliances between two states in the U.S. is 7.32 and the median is 1, which suggests that variable *Number of alliances* is very skewed. 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. We also collect data on the number of firms by business size class from the Census Bureau's Statistics of U.S. Businesses. We count the number of firms with >100 employees (due to better data coverage) for each state-year and then average it over our sample period by state. We then scale the number of actual alliances between two states by the number of potential alliances (i.e., the number of firms in one state times the number of firms in another state within a

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

state-pair) to construct *Alliance Intensity*. To align the order of magnitudes between the numerator and the denominator, we divide the number of potential alliances by a million.

4. 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 et al., 1998; Robinson, 2008; Li et al., 2019). However, unlike M&As, incomplete contracting is a serious challenge alliances face. For example, 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 ex post cooperation is needed but it is impossible or expensive to design (or enforce) complete contracts ex ante, which is the case when forming alliances. This is the basis for *H1*, which we test in this section.

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 et al., 2012; McGuire et al., 2012; Di Giuli and Kostovetsky, 2014; Hasan et al., 2017; Hayes et al., 2021; Hoi et al., 2019; Pan et al., 2020). Similarity in local culture where partnering firms reside, shaped by historical immigration, could thus lead to shared beliefs and preferences between partnering firms' stakeholders, which mitigate the

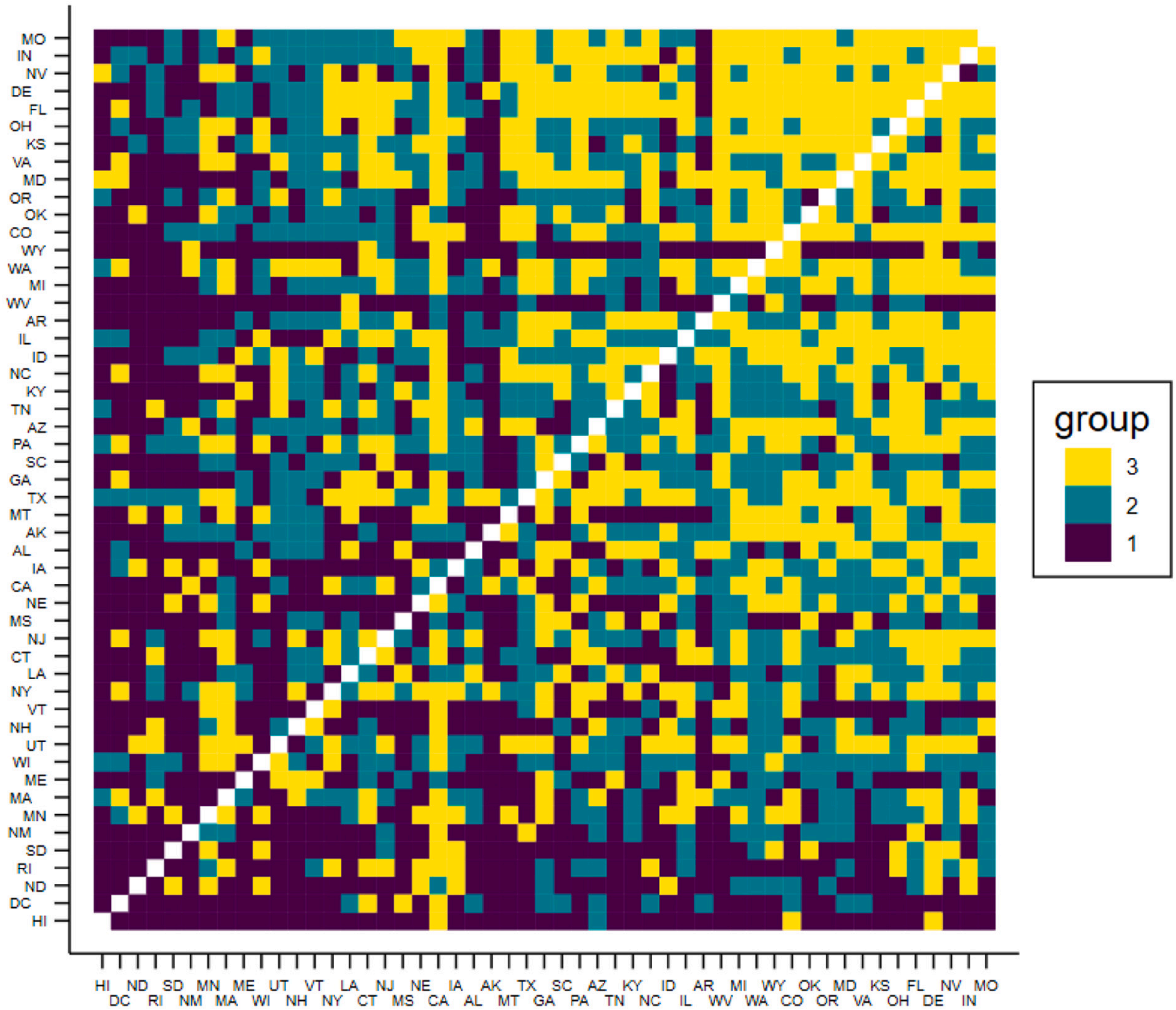

Fig. 3. Heat map of number of alliances and ancestral connections.
This figure plots alliance intensity (upper triangle) and ancestral connections (lower triangle) between all state pairs within the U.S. Alliance intensity and ancestral connections are ranked into three groups with group three means high alliance intensity 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.

hold-up problem by reducing information friction and facilitating cooperation. We test the effect of ancestral connection on alliance formation in this section.

4.1. State-level analysis

4.1.1. Baseline results

In Fig. 3, we plot the heat map of *Alliance Intensity* between state pairs in the upper triangle and ancestral connections between state pairs in the lower triangle. Darker (lighter) color represents less (more) intensive 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 intensity and ancestral connection. Some states, such as California, have higher alliance intensities 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:

$$\begin{aligned} Alliance\ Intensity_{ij} = \alpha_0 + \beta_1 Ancestral\ Distance_{ij} + \beta_2 Border_{ij} + \beta_3 Geographic\ Distance_{ij} \\ + \beta_4 Ind\_diff_{ij} + \beta_5 Female_{diff_{ij}} + \beta_6 Age\_diff_{ij} + \beta_7 College\_diff_{ij} + \epsilon_{ij.} \end{aligned}$$

where subscripts i and j denote the two states in the pair. We form 1275 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 4.2, 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 2 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 intensity of alliances formed by partners located in a pair of states and the ancestral distance between this state pair. 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 0.032 increase of (scaled) alliance intensity, similar to the increase in alliance intensity (0.048) if the two states border each other.

In Column (6), instead of *Ancestral Distance,* we use *Largest Overlap*, which measures the largest overlap in ancestral fractions between two states. Consistent with the negative correlation between *Ancestral Distance* and alliance intensity in the baseline, we find a significant, positive correlation between *Largest Overlap* and the number of alliances.

Although it is hard to pin down the exact channel for the effect of ancestral connection, we revisit the conjecture that it may influence the degree of shared ideologies. Strategic alliances are often modeled as prisoner's dilemma (or assurance/coordination games). Shared norms and preferences could serve as a means to coordinate which equilibrium to select and more generally facilitate collaboration between local employees (and between stakeholders) of the partnering firms. Giuliano and Tabellini (2020) document that historical immigration to the U.S. is associated with political ideology today. In Section 3.1, 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. Fig. 4 plots both the direct effect of ancestral distance on alliance intensity, 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.

4.1.2. Robustness tests

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 4 column (1), we continue to find similar results as those in Table 2 column (2). 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 (Seegert, 2015, 2016). In Appendix 4 column (2), we find that the results are unaffected. Third, we re-

Table 2
Ancestral distance and alliance formation.

	(1)	(2)	(3)	(4)	(5)	(6)
			Alliances Intensity > 0	excl. DE		
Ancestral Distance	−0.135***	−0.114**	−0.199**	−0.109**	−0.098**	
	(0.043)	(0.053)	(0.077)	(0.053)	(0.045)	
Largest Overlap						0.230**
						(0.096)
Border		0.062***	0.051**	0.058**	0.048***	0.061***
		(0.020)	(0.022)	(0.024)	(0.018)	(0.018)
Geographic Distance		−0.012**	−0.009	−0.017**	−0.006	−0.010**
		(0.006)	(0.006)	(0.007)	(0.007)	(0.005)
Ind_diff		−0.172***	−0.251***	−0.175***	−0.171***	−0.176***
		(0.054)	(0.089)	(0.056)	(0.053)	(0.054)
Female_diff					0.003	0.001
					(0.012)	(0.012)
Age_diff					−0.027***	−0.027***
					(0.009)	(0.009)
College_diff					−0.016**	−0.017**
					(0.007)	(0.007)
State FEs		Yes	Yes	Yes	Yes	Yes
Double cluster	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1275	1246	770	1197	1246	1246
Adjusted R-squared	0.030	0.528	0.493	0.541	0.552	0.549

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

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

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.

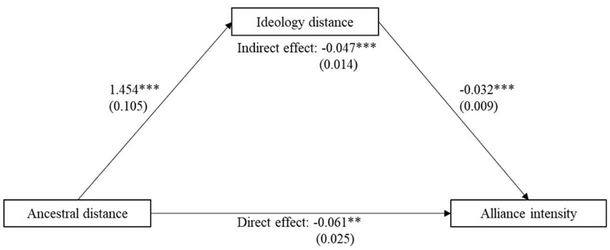

Fig. 4. Path diagram.
This figure plots the path diagrams of the direct and indirect effects of ancestral distance on alliance intensity. The mediating variable is Ideology distance. Bootstrapped standard errors are reported in parentheses.

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 toward each other (Bornhorst et al., 2004). We find, in Appendix 4 column (3), consistent results using the ancestral distance calculated based on the broader ancestry categories as those in Table 2. Fourth, in Appendix 4 column (4), we report a specification using the 2010 Census instead of 1980 Census. Results remain similar. Finally, we report results using L2-norm distance measures instead of L1-norm measures, in Appendix 4 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.

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 2 at the county level. Results are reported in Appendix 5.

The first column in this table uses the whole sample (3136 counties) to construct county-pair observations. We control for whether the two counties are adjacent, county fixed effects, as well as 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, in column (1), we find a significant and negative correlation between county-level ancestral connection and the alliance intensity between the two counties. The large number of county-pair observations highlights the challenge of dimensionality with finer-level analysis. In column (2), 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.

4.2. Historical immigration shocks

The identification relies on the extent to which ancestral connection is determined by historical immigration patterns. To capture the supply-push component of historical immigration, we exploit exogenous variation in immigration to U.S. cities, induced by WWI and the 1921 and 1924 Immigration Acts (Tabellini, 2020).

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 variable based on historical immigration shocks, noting the fact that immigrants' location decision typically follows pre-existing settlement patterns (Stuart and Taylor, 2021). 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, this variable based on historical shocks 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 effect of immigrant inflows in the presence of unobserved city-specific demand shocks (e.g., those related to economic conditions). More specifically, this variable 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).[14] 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 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 3, we use this variable, *Ancestral Distance (supply-push)*, to instrument for our baseline *Ancestral Distance*. The relevance condition is supported by the strong first-stage F-statistics. We acknowledge that we cannot directly test the exclusion restriction, and it is possible that *Ancestral Distance (supply-push)* could have had an impact on historical economic activities, which in turn could affect today's alliance formation. With this caveat, we conduct a 2SLS analysis to confirm the role of ancestral connection on alliance intensity.

In columns (1) and (2), we use city fixed effects and include an indicator that equals to one if the two cities are in the same state. In Columns (3) and (4), we use state-pair fixed effects in addition. We find that a one-standard-deviation increase in ancestral distance between two cities is associated with a decrease in (scaled) alliance intensity by 1.40, compared to its sample mean of 0.50 (and standard deviation of 9.45). 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 or changing fixed effects does not change the coefficient on ancestral connections much. Overall, the results in this subsection further support the positive relation between ancestral connection and alliance intensity.

4.3. Deal-level analysis

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 et al., 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, Panel A 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

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

Table 3
City-level ancestral distance and alliances.

	(1)	(2)	(3)	(4)
	First-stage	Second-stage	First-stage	Second-stage
Dependent	*Ancestral Distance*	*Alliance Intensity*	*Ancestral Distance*	*Alliance Intensity*
Ancestral Distance (supply-push)	6.242***		3.598***	
	(0.719)		(0.363)	
Ancestral Distance		−3.007**		−4.229*
		(1.227)		(2.256)
Same State (both partners)	−0.299***	0.165		
	(0.053)	(0.884)		
First-stage F-stat	75.65		97.98	
City FEs	Yes	Yes	Yes	Yes
State-pair FEs			Yes	Yes
Double cluster	Yes	Yes	Yes	Yes
Observations	14194	14194	13968	13968
Adjusted R-squared	0.532	0.001	0.703	0.004

This table reports coefficient estimates and standard errors from regressions of alliance intensity on *Ancestral Distance* between each city pair and control variables. The *Ancestral Distance* between a pair of cities is instrumented using 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:

$$Alliance\ Intensity_{ij} = \alpha_0 + \beta_1 Ancestral\ Distance_{ij} + \beta_2 Same\ State_{ij} + \epsilon_{ij}$$

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.

forming an alliance increases by 1.7%, compared to the unconditional probability of forming alliances (9.5%) in this sample. 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, sales growth, as well as similarity in patents (Li et al., 2019). Firms with smaller differences in characteristics (e.g., CapEx and leverage), and those with more similar patents are more likely to form alliances. But controlling for differences or similarities in firm characteristics does not qualitatively change the relation between *Ancestral Distance* and the probability of the two firms to form an alliance.

In Panel B, to study the role of ancestral connection in mitigating holdup problems, we partition the sample using two measures for the degree of potential holdup problems between the partners. In columns (1) and (2), we construct two indicator variables, which equals one if *Vertical Relatedness* that measures the vertical relatedness between partners based on their product descriptions (Frésard et al., 2020) is above (below) the sample median. In Columns (3) and (4), we define two indicator variables 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 mainly driven by alliances between firms that are more vertically related and alliances from industries that rely more on relationship-specific investment, both of which are more likely to suffer from the hold-up problem, as suggested by the negative and significant coefficient on *Ancestral Distance*High Holdup*.

Together, the findings in Section 4 provide strong support for *H1* and suggest that ancestral connection shaped by historical immigration patterns could facilitate alliance formation and hence be a deep cultural root for firm boundaries in the U.S. today.

5. Alliance performance

5.1. Ancestral connections and announcement abnormal returns

If ancestral connection indeed induces shared values and beliefs, which mitigates the problems with incomplete contracting such as the hold-up or prisoner's dilemma, we expect better alliance performance formed by partners from well-connected places. More generally, ancestral connection could increase the synergy created by the alliance, via better collaboration or information sharing, similar to the role of intangible family assets in family firms. In this section, we examine the relation between ancestral distance and the combined abnormal announcement returns of partners, to test *H2*. Ancestral connection could be a proxy for "cultural fit" or "similarity in values" mentioned in announcements of alliance formation (see Footnote 2 for examples). 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:

Table 4
Propensity of forming alliance.

Panel A			
	(1)	(2)	(3)
Ancestral Distance	−0.039**	−0.054**	−0.061***
	(0.018)	(0.022)	(0.023)
Border	0.000	0.003	−0.007
	(0.015)	(0.018)	(0.018)
Geographic Distance	0.014***	0.021***	0.019***
	(0.004)	(0.006)	(0.006)
Ind_diff	−0.025	−0.067***	−0.052**
	(0.017)	(0.021)	(0.022)
Female_diff	−0.013	−0.021*	−0.017
	(0.010)	(0.012)	(0.012)
Age_diff	−0.003	−0.004	−0.004
	(0.003)	(0.003)	(0.003)
College_diff	−0.003*	−0.004	−0.002
	(0.002)	(0.002)	(0.002)
CapEx_diff			−0.417***
			(0.128)
RD_diff			−0.009
			(0.039)
ROA_diff			0.025
			(0.022)
Cash_diff			0.033
			(0.025)
TobinQ_diff			0.006*
			(0.003)
Assets_diff			−0.075***
			(0.010)
SalesGrowth_diff			−0.004
			(0.004)
Leverage_diff			−0.048**
			(0.023)
Patent Similarity			0.156***
			(0.020)
Deal FE		Yes	Yes
Cluster by deal		Yes	Yes
Observations	5188	5188	4616
Adjusted R-squared	0.004	0.044	0.062

Panel B				
	(1)	(2)	(3)	(4)
Holdup measure:	*Vertical relatedness*	*Vertical relatedness*	*Relationship-specific investment*	*Relationship-specific investment*
Ancestral Distance×Low Holdup	−0.024	−0.037	−0.021	−0.038
	(0.027)	(0.029)	(0.031)	(0.032)
Ancestral Distance×High Holdup	−0.087***	−0.096***	−0.077***	−0.077***
	(0.032)	(0.032)	(0.028)	(0.029)
High Holdup	0.068**	0.071**		
	(0.032)	(0.034)		
Border	−0.005	−0.009	0.003	0.000
	(0.018)	(0.019)	(0.018)	(0.019)
Geographic Distance	0.019***	0.019***	0.022***	0.021***
	(0.006)	(0.007)	(0.006)	(0.006)
Ind_diff	−0.059***	−0.057**	−0.069***	−0.062***
	(0.022)	(0.024)	(0.021)	(0.023)
Female_diff	−0.016	−0.014	−0.023*	−0.019
	(0.012)	(0.013)	(0.012)	(0.013)
Age_diff	−0.006*	−0.005	−0.004	−0.003
	(0.003)	(0.004)	(0.003)	(0.004)
College_diff	−0.003	−0.003	−0.004	−0.005*
	(0.002)	(0.002)	(0.002)	(0.002)
CapEx_diff		−0.427***		−0.412***
		(0.128)		(0.128)
RD_diff		−0.011		−0.010

(*continued on next page*)

Table 4 (*continued*)

Panel B				
	(1)	(2)	(3)	(4)
Holdup measure:	*Vertical relatedness*	*Vertical relatedness*	*Relationship-specific investment*	*Relationship-specific investment*
		(0.041)		(0.039)
ROA_diff		0.028		0.024
		(0.023)		(0.022)
Cash_diff		0.029		0.034
		(0.026)		(0.025)
TobinQ_diff		0.006*		0.006*
		(0.004)		(0.003)
Assets_diff		−0.081***		−0.075***
		(0.011)		(0.010)
SalesGrowth_diff		−0.004		−0.004
		(0.004)		(0.004)
Leverage_diff		−0.048**		−0.050**
		(0.024)		(0.024)
Patent Similarity		0.161***		0.156***
		(0.020)		(0.020)
Deal FE		Yes	Yes	Yes
Cluster by deal		Yes	Yes	Yes
Observations	4937	4461	5178	4612
Adjusted R-squared	0.059	0.078	0.045	0.062

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. *High (Low) Holdup* is an indicator for above (below) median *Holdup*. In Panel B, columns (1) and (2), *Holdup* is measured as *Vertical Relatedness* between the pair of partners following Frésard et al. (2020). In columns (3) and (4), *Holdup* is measured as *Relationship-specific Investment* for an industry following Nunn (2007). Standard errors double clustered by deal 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.

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

where i and j denote the states in which the partners reside, and k denotes the deal k. While we focus on deals with partnering firms from different states in the rest of the paper, to maximize sample size, here we start with 901 deals with available *CAR*, including same-state deals, while setting ancestral distance to be 0 for same-state deals.[15]

In column (1) of Table 5, 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.

We report several robustness checks in the appendices. In Appendix 6, we use different asset pricing models and a different length of the event window, to estimate abnormal announcement returns. In Appendix 7, we examine the relationship between county-level ancestral distance and announcement returns. Results remain similar. Finally, in Appendix 8, 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. Overall, our results support *H2* that higher ancestral connection is associated with better performance.

5.2. Non-executive key employees vs. corporate leaders

The labor markets for both executives (Yonker, 2017; Ma et al., 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

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

Table 5
Announcement returns.

	(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

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.

partners' patent inventors, *Ancestral Distance_inventors*, as defined in Section 3. 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 6, we find that ancestral distance between inventors is negatively related to announcement abnormal returns only when the alliances are related to R&D activities. Ancestral connection could facilitate knowledge transfer, which might be subject to hold-up given its "sunk cost" nature.

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 Xuan, 2014). We thus measure the ancestral distance between corporate leaders as well. We include an indicator variable that equals one if CEOs of partners have the same ancestral origin, *Same Origin_CEO*, and the ancestral distance between the boards (including the CEOs) of the partnering firms, *Ancestral Distance_Board*, as defined in Section 3. To maximize the sample for this test, we again start with deals with available announcement abnormal returns and available information on corporate leaders' ancestries, including same-state deals with ancestral distance set to be 0.

In Column (2) and (3) of Table 7 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 3, 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 7 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

Table 6
Ancestral distance between inventors.

	(1)	(2)	(3)
Dependent	*CAR*	*CAR*	*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

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.

(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. Broadly speaking, our analysis here addresses the call by Fan et al. (2022) for future research on the role of culture in governing stakeholder relationships.

6. Alliance location choice

One 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.[16] Interestingly, on average, when the alliance is located outside both partners' states, the ancestral distance between the alliance's location and the 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 8, 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. This result supports *H3* that the venture location decision may be driven by concerns about eliciting cooperation or informational friction, which is more likely an issue when the ancestral distance is larger. In this case, partnering firms may be reluctant to give the other party proximity advantage to the new venture, leading to a location choice outside of both partners' states. 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

[16] 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.

Table 7
Ancestral distance between corporate leaders.

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 for out-of-state deals

	(1)	(2)	(3)	(4)
Dependent	*CAR*	*CAR*	*CAR*	*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

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.

Table 8
In-state and out-of-state ventures.

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	8434	8434
Adjusted R-squared	0.168	0.187

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 (partner and new venture)* 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.

Table 9
New venture location

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	126447	126446	126447
Adjusted R-squared	0.008	0.060	−0.010

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.

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 9, 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 supports *H4*: 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 and the problems with incomplete contracting may be more severe. 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. This result highlights the importance of cultural determinants in location decisions, more than geographic distance.

7. 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 reduce transaction costs in alliance formation, similar to the role of "family assets" in family firms (Bennedsen and Fan, 2014; Bennedsen et al., 2015; Fan et al., 2022). 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, is significantly associated with an increase in alliance intensity 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 partners' states is strong, 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 transaction costs and shaping firm boundaries, above and beyond geographic boundaries. Our results thus support the 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 et al., 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.

Data availability

The authors do not have permission to share data.

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

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

	Ancestry group		Ancestry group
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
90	Ugandian	115	Fijian, New Guinean, American Samoan, Tokleau Islander, Guamanian, Chamarro, Marshallese, Carolinian, Melanesan, Micronesian, Polynesian, Pacific Islander, 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
108	Ceylonese, Burmese, Okinawan, 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

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(*continued*)

Panel B: 10 categories of broader ancestry group	
	Broader ancestry group
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:	
Number of Alliances	The number of alliances between the state pairs over the sample period.
Alliance Intensity	The number of alliances between the state pairs divided by the number of potential alliances, which is the product of the average numbers of firms with >100 employees of the state pairs over the sample period divided by a million.
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): $Ancestral\ Distance_{x,y} = \sum_{i=1}^{138} \mid x_i - y_i \mid$
Largest Overlap	The largest overlap in ancestral fractions between two states
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 (both partners)	An indicator variable that equals one if the alliance partners are from the same state, and zero otherwise.
Same state (partner and new venture)	An indicator variable that equals one if the new venture is located in at least one of the partners' 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.

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Variables	Descriptions
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.
CapEx_diff	The absolute difference between the partners' capital expenditure scaled by total assets.
RD_diff	The absolute difference between the partners' R&D expenditure scaled by total assets
ROA_diff	The absolute difference between the partners' return on asset that is the net income divided by total assets.
Cash_diff	The absolute difference between the partners' cash holdings that is the cash and cash equivalents divided by total assets.
TobinQ_diff	The absolute difference between the partners' Tobin's Q that is (total assets – book value of equity + market value of equity)/total assets.
Assets_diff	The absolute difference between the partners' sizes that is measured as the logarithm of total assets.
SalesGrowth_diff	The absolute difference between the partners' sales growth that is the change in sales divided by lagged sales.
Leverage_diff	The absolute difference between the partners financial leverage that is the total debt divided by the sum of total debt and the market value of equity.
Patent Similarity	The cosine similarity between two vectors characterizing the partners' patent output. We collect the fractions of patent applications submitted in year t-2 to year t in different patent classes to form the vector of patent output.
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.
Vertical Relatedness	The potential for vertical relatedness for firm pairs based on their product descriptions as in Frésard et al. (2020).
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 (2012).
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 (2012).
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. Ancestral distance and political attitudes

	(1)	(2)	(3)	(4)
Dependent	Δ*Republican share*$_{it}$	Δ*Republican share*$_{it}$	Δ*Republican share*$_{it}$	Δ*Republican share*$_{it}$
Δ*AC weighted Sinclair*$_{it}$	0.499** (0.208)	0.462** (0.203)	0.429** (0.188)	0.456** (0.202)
Δ*Sinclair*$_{it}$		0.007** (0.003)		
Δ*Geo. weighted Sinclair*$_{it}$			0.094 (0.075)	
Δ*FB weighted Sinclair*$_{it}$				0.009* (0.004)
Year FEs	Yes	Yes	Yes	Yes
State-year FEs	Yes	Yes	Yes	Yes
State cluster	Yes	Yes	Yes	Yes
Observations	15,518	15,518	15,518	15,518
Adjusted R-squared	0.746	0.746	0.746	0.746

This table reports coefficient estimates and standard errors from regressions of change in pollical attitudes on Δ*AC weighted Sinclair* and control variables. Δ*Republican share* 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. *ΔSinclair* is the first difference of *Sinclair*, an indicator variable for whether Sinclair has entered the county during an election cycle. *ΔAC weighted Sinclair* uses the ancestral connection (two minus ancestral distance) between county pairs to weigh the indicator variable *ΔSinclair* for all other 3103 counties. *ΔGeo. weighted Sinclair* and *ΔFB weighted Sinclair* use the inverse of geographic distances and Facebook connections (see Bailey et al. (2018) for details) between county pairs as the weights, respectively. The sample includes five presidential election data over 2000 to 2016. Specifically, we estimate the following model using pooled regressions with year and state-year 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 state 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.

Appendix 4. Robustness tests

	(1)	(2)	(3)	(4)	(5)
Dependent	*Alliance Intensity*				
Ancestral Distance	−0.131**	−0.065**			
	(0.062)	(0.032)			
Ancestral Distance$_{10}$			−0.113**		
			(0.044)		
Ancestral Distance$_{2010}$				−0.153**	
				(0.059)	
Ancestral Distance$_{L2}$					−0.176**
					(0.080)
Border	0.049**	0.051***	0.060***	0.039**	0.062***
	(0.020)	(0.017)	(0.020)	(0.017)	(0.018)
Geographic Distance	−0.013**	−0.006	−0.009	0.000	−0.009*
	(0.006)	(0.007)	(0.005)	(0.009)	(0.005)
Ind_diff	−0.178***	−0.168***	−0.170***	−0.173***	−0.176***
	(0.059)	(0.052)	(0.053)	(0.053)	(0.055)
Female_diff		−0.001	0.001	0.000	0.003
		(0.013)	(0.012)	(0.014)	(0.013)
Age_diff		−0.025***	−0.027***	−0.024***	−0.028***
		(0.009)	(0.010)	(0.008)	(0.010)
College_diff		−0.015**	−0.017**	−0.015**	−0.017**
		(0.007)	(0.007)	(0.007)	(0.007)
HHI_diff		−0.345**			
		(0.171)			
Tax_diff		−0.005			
		(0.005)			
State FEs	Yes	Yes	Yes	Yes	Yes
Double cluster	Yes	Yes	Yes	Yes	Yes
Observations	1013	1246	1246	1246	1246
Adjusted R-squared	0.564	0.556	0.551	0.557	0.548

This table reports coefficient estimates and standard errors from regressions of *alliance intensity* 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.

Appendix 5. County-level ancestral distance and alliances

	(1)	(2)
		Number of Alliances > 0
Ancestral Distance	−0.0001**	−0.062**
	(0.000)	(0.025)
Adjacent County	0.004***	0.061***
	(0.001)	(0.023)
Geographic Distance	0.000	0.019
	(0.000)	(0.032)
Ind_diff	−0.002***	−0.252***
	(0.000)	(0.057)
Female_diff	0.003**	0.109
	(0.001)	(0.353)
Age_diff	0.000***	0.000
	(0.000)	(0.001)
College_diff	−0.018***	−0.237**
	(0.003)	(0.102)
County FEs	Yes	Yes
State-pair FEs	Yes	Yes
Double cluster (state)	Yes	Yes
Observations	4,763,239	3805
Adjusted R-squared	0.010	0.788

This table reports coefficient estimates and standard errors from regressions of *alliance intensity* on *Ancestral Distance* between each county pair and control variables. We take the logarithm of one plus *Alliance Intensity* to reduce the skewness of the dependent variable in this sample. Specifically, we estimate the following model using pooled regressions with county and state-pair fixed effects:

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

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.

Appendix 6. Alternative measures of announcement returns

	(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

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.

Appendix 7. County-level ancestral distance and announcement returns

	(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

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.

Appendix 8. Changes in operating performance

	(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

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.

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