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Linguistic distance and mergers and acquisitions: Evidence from China

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ABSTRACT

We use a new measure of linguistic distance and examine how it relates to the wealth effects of mergers and acquisitions using a sample of acquisitions in China. Linguistic distance between the acquirer and the target is constructed based on the map that defines the difference in level between any pair of languages in China. We find a significant negative relationship between the linguistic distance and the acquirer's abnormal return around the announcement. The findings are robust to different model specifications, institutional differences in local financial development, and after accounting for multicollinearity between linguistic and geographical distances and the potential social networks between acquirers and targets. The negative effect of linguistic distance is more pronounced when: (1) the deals are not in high-tech industries, (2) acquirers are not from Putonghua popular areas, and (3) acquirers are not from a linguistically diverse area. Further analysis suggests that top management's dialect experience is valuable to the acquirer's shareholders in mergers and acquisitions. Our findings suggest that cultural distance matters in corporate decisions.

1. Introduction

Mergers and acquisitions (M&As) are among the largest investments made by firms. The literature shows that, on average, the acquirers do not create value for their shareholders through M&As (Andrade et al., 2001, and Moeller et al., 2005). Studies examine this issue under the framework of agency cost (Jensen, 1983, and Masulis et al., 2007), social network (Ishii and Xuan, 2014), political ideology (Elnahas and Kim, 2017), CEO overconfidence (Malmendier and Tate, 2008; Bogan and Just, 2009), and market timing (Anderson et al., 2017; Moran, 2017).[1] Our work contributes to the existing literature on the negative value to acquirers from a different perspective: cultural friction. More specifically, we measure the linguistic distance between the acquirer and the target and take it as a cultural friction in this context.

Humans learn their culture through language, and language in turn shapes human economic behavior (Lazear, 1999 and Chen,

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[1] For instance, Masulis et al. (2007) find that acquirers with more anti-takeover provisions exhibit lower M&A announcement returns. Ishii and Xuan (2014) document that the extent of social connection between the acquirers' directors and senior executives with the targets has a negative impact on the M&A announcement returns. Malmendier and Tate (2008) document that overconfident CEOs overpay for their targets and undertake value destroying M&As. In a study of CEO's financial contributions to identify their political ideology, Elnahas and Kim (2017) find no evidence that political ideology creates value in the short run. Moran (2017) shows that, during merger waves, dispersion in acquirers' post-merger performance declines along the merger wave.

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2013). A growing literature examines the impact of a language, such as, on the asset allocation (Grinblatt and Keloharju, 2001, Beugelsdijk and Frijns, 2010, Anderson et al., 2011, and Aggarwal et al., 2012), corporate strategies (Joshi and Lahiri, 2014, and Cuypers et al., 2015) and firms' relationship with their shareholders (Brochet et al., 2016). Few works investigate whether language could be an issue in a firm's investment decision. We fill the gap by studying whether and how the linguistic distance between the acquirer and the target affects the acquisition performance.

Language plays two roles in M&As. First, it is a tool of communication. Language could cause barriers or frictions in negotiations or communications (Joshi and Lahiri, 2014, and Brochet et al., 2016). Second and more importantly, a language is the carrier of culture, and it can be viewed as one of the important familiarity attributes, such as geography and culture (Beugelsdijk and Frijns, 2010; Anderson et al., 2011, and Aggarwal et al., 2012). To access reliable information and evaluate the synergy gains from mergers, acquirers need to negotiate and communicate with the targets before any deal is announced. Language difference creates considerable cultural frictions in interactions and may generate misunderstanding or misevaluation of the targets or the potential synergies (Joshi and Lahiri, 2014), resulting in value-destroying acquisitions or overpaying to the targets. Synergy gains in M&A require post-merger coordination between the employees of each firm (Ahern et al., 2015). Employees are usually hired locally. They are involved in the local cultural environment and speak the local language when they are at work. Culture distance, in our paper, measured as the linguistic distance, is a friction or barrier for the involved parties. It generates impediments such as mistrust, misunderstanding, or mismatched goals and thereby reduces the coordination effectiveness. Thus, from the perspective of the acquirer's shareholders, they will favor less the targets that have greater cultural distance from acquirers because the uncertainty in the valuation and the expected difficulty of post-merger integration could be harmful to their wealth.

We empirically examine our hypothesis using a sample of 543 completed domestic acquisitions in China between 2000 and 2012. There are mainly two reasons why we are interested in China. First, China has more than 5000 years of history. Language diversity is not an exception but rather a norm. The geographic segmentation and linguistic diversity in China provides a good opportunity to measure the difference between two dialects in a precise way. In fact, we find only 46% of deals in our sample occur between two firms located in the same dialect language area. Second, with a fast economic growth and development, China has a good number of M&As. It provides a good setting to understand how culture affects corporate decisions in an emerging market.

Our findings suggest that the greater is the linguistic distance between the acquirers and the targets, the lower the announcement returns are. The findings are robust to different model specifications, institutional differences in local financial development, and after accounting for multicollinearity between linguistic and geographical distances and the social networks between acquirers and targets. In further analysis, we explore whether the linguistic distance effect displays any cross-sectional variations as our hypothesis would predict. If a language generates frictions and affects the merger process, we expect to have a stronger effect in deals that could rely more on the language and be more affected by the language frictions. To test our conjecture, we partition the sample based on (1) whether the acquisitions occur in the high-tech industries; (2) acquirer's geographic differences in Putonghua Proficiency; and (3) acquirer's geographic differences in linguistic diversity. Consistent with our predictions, we find the effect of linguistic distance is more pronounced if it is not a high-tech merger, if the acquirer is operated in a region where Putonghua is less popular, or where linguistic diversity is low. Our results suggest that the language effect is related to the firm-level characteristics and the institutional environment as well.

To specify a channel through which the cultural friction could exist, we examine the acquirer CEO's dialect background and dialect experience. If the acquirer's CEO is unfamiliar with the cultural environment of the regions where the target is located, he cannot smoothly communicate with the target firm. Then, he may misunderstand the value of the merger and make a value-destroying decision. We test this conjecture by constructing several measures on the acquirer CEO's dialect experience. Our findings support our argument.

Our study contributes to a growing literature on culture and finance (see Karolyi, 2016). For example, Stulz and Williamson (2003) find that the principal religion can better explain variations in the creditor rights across countries. Guiso et al. (2008) focus on trust as a cultural attribute for stock market participation. Chui et al. (2010) focus on differences in one cultural dimension-individualism, which they link to overconfidence and self-attribution cognitive biases, for the stock return of momentum strategies. Eun et al. (2015) study individualism and stock price synchronicity. Siegel et al. (2011) and Ahern et al. (2015) examine cultural distance between two countries and international investment flows.

Specifically, we shed light on this stream of literature in several ways. First, we introduce a new measure of culture distance. Linguistic distance, a quantitative measure of how one dialect is different from another, reflects in the context of cultural distance. Second, few studies have examined the impacts of culture on a firm's investment decision and investment outcome (Ahern et al., 2015). Our results suggest that culture matters in M&A outcomes. A firm should make a careful decision if it wants to integrate another firm with a different cultural background. This study is also related to Cuypers et al. (2015), who study the linguistic distance between the acquirer and the target and its effect on the percentage of ownership an acquirer takes in a cross-border acquisition context. Our work differs from theirs in several respects. First, our study focuses on one country – China rather than multiple countries. We take the advantage of the unique linguistic diversity in China while avoiding considering any unobservable country-level differences in cross-border merger and acquisition studies. Second, Cuypers et al. (2015) measure the linguistic distance based on whether the official language spoken in the acquirer's and target's country belongs to the same language family. The authors use a (1, 0) dummy variable to capture the impact of linguistic difference. In contrast, our measure is a continuous variable that depicts the extent of difference between an acquirer and the target in their language environment. That is, we use an improved and a more precise linguistic distance measure. Third, we examine the acquisitions through the market reaction around the announcement days, which reflects shareholders' opinions on whether the linguistic distance generates synergies from mergers or frictions in the merger process.

The reminder of the paper is organized as follows. Section 2 discusses the data and methodology and reports summary statistics. Section 3 reports the main empirical findings. Section 4 concludes.

2. Data and methodology

2.1. Sample

This paper studies the domestic mergers and acquisitions in China announced between Jan 1, 2000 and Dec 31, 2012. Given almost no firms acquired during the sample period were publicly traded, the target firms in our sample are all private by nature. The M&A transaction data are extracted mainly from the WIND database, combined with those in the China Stock Market and Accounting Research (CSMAR) database and RESSET.[2]

We exclude deals in which acquiring firms and targets are related parties[3] or deals in financial industries. Following Lehn and Zhao (2006) and Masulis et al. (2007), we require an acquisition in our sample to satisfy (1) the acquisition is completed; (2) the deal value is more than 1 million RMB; (3) the acquirer controls less than 50% of the target prior to the acquisition announcement and more than 50% after; (4) the annual financial statement information, stock return data, and deal-level information are available in the China Stock Market and Accounting Research (CSMAR) database; (5) the physical location of the firms (i.e., headquarter) can be identified from the CSMAR.

Our final sample comprises 543 acquisitions made by 448 firms. Panel B in Table 1 presents the distributions of all the transactions by sectors defined by the China Securities Regulatory Commission (CSRC). Almost one half of the deals occurred in the manufacturing sectors. In an untabulated table with the distribution of all acquisitions by industries, the top five industries classified as a two-digit CSRC code with the highest number of acquirers are Real Estate (11.61%), Pharmaceutical Manufacturing (6.47%), Retailer (5.80%), Chemicals and Chemical Products (4.91%) and Electrical Machinery and Equipment (4.46%).

2.2. Linguistic distance (LD) measure

Our key variable is the measure of the dialect language distance between the acquiring firm and the target firm in a deal, named *LD*. We identify the dialect area that the acquirer (target) belongs to by matching its physical location (at the time of announcement) with the language map in the "The Language Atlas of China" (hereafter, the Atlas) edited by the Chinese Academy of Social Sciences.[4] For example, if a firm is headquartered in Guangzhou, then by looking at the distributions of the dialect language of China in the Atlas, we know the firm is operated in the "Cantonese" area. Since the dialects can be allocated to city or even county level by Atlas, all the firms in our sample can be identified with only one type of the dialect language. The Atlas mainly divides all the dialects into nine different groups, i.e., Mandarin, Jin, Gan, Hui, Min, Goetian (Wu-Chinese), Xiang, Cantonese and Hakka. The Mandarin can be further divided into Beijing, Northeastern, Jilu, Jianghuai, Jiaoliao, Lanyin, Shuthwestern, and Zhongyuan Mandarin eight sub-categories. Therefore, this paper uses 16 basic types of dialect language, including 8 different types of Mandarin and 8 types of dialects other than Mandarin. Table 1 (Panel A) describes the distribution of the dialects both among the acquirers and the targets in our sample.

Then, we calculate the language distance between the acquirer and the target firms using the matrix constructed by the Atlas that measures the bilateral distance between each pair of the dialects/languages mentioned in the Atlas. These dialects differ from each other in sound, grammar, or/and meaning, causing barriers in communication between people from different regions. In the Atlas, the distance is measured as a number ranging from 0 to 5 with a larger number meaning longer linguistic distance between two dialect languages.[5] In other words, it is more difficult for people speaking in a type of dialect to understand people speaking in another type of dialect if the *LD* defined is higher.

Appendix B provides the matrix of 16 major dialects in China and their bilateral distances demonstrated by the Atlas. It is interesting to find that for any specific dialect, its distance to another dialect varies depending on which dialect it compares to. It has some dialects that sound close to each other (i.e., distance = 1) while other dialects are quite different between them in terms of the phonetics, morphology or syntax (i.e., distance = 5). The average distance calculated for the 16 major dialects tells that Cantonese seems to be the most isolated dialect in the family while the southwestern Mandarin is the most common one., By carefully depicting the linguistic distance among different local Chinese languages, we provide a more accurate measure of the cultural difference between acquirer and target firms than the dummy variable measure as described in Cuypers et al. (2015).

Tables 1 and 2 provide the dialect language distribution of the acquirers (the targets) of the deals from 2000 to 2012 and the distribution of the language distance between the acquirers and the targets, respectively. Acquirers sharing a common dialect with the target represent 46% of the total deals, which indicates that acquisitions are more likely to occur between two firms with no

[2] These are three leading financial databases that focus on China and are widely used in recent studies related to China, for example, Huang and Zhu (2015), Liao et al. (2014), Liu and Tian (2012), etc.

[3] For example, we exclude the deals in which the acquirer controls the private target, holds shares in the private target, or was the parent company of the target before the acquisition announcement.

[4] Other studies using this language map include Chang et al. (2015), who examine how language diversity in China affects trading behavior on the stock market.

[5] Dialects in the Atlas are first categorized into different groups, then within each group, further categorized them into sub-groups, and last within each sub-group can be categorized into sub-subgroups. The distance is 0 if the two dialects belong to the same sub-subgroup, is between 1 and 3 if the two dialects belong to the same subgroup but not to the same sub-subgroup and is 3 to 5 if the two dialects do not belong to the same group.

Table 1
Dialect distribution.
Panel A exhibits the dialect language distribution for both acquirers and targets of 543 domestic M&A in Mainland China announced between 2000 and 2012. Panel B shows the distribution of the transactions by sectors (defined by CSRC).

Panel A: Distribution by type

Type of dialect language	Acquirers		Targets	
	N	%	N	%
Beijing Mandarin	75	13.81%	60	11.05%
Northeastern Mandarin	17	3.13%	22	4.05%
Jilu Mandarin	20	3.68%	22	4.05%
Jianghuai Mandarin	38	7.00%	29	5.34%
Jiaoliao Mandarin	18	3.31%	17	3.13%
Lanyin Mandarin	7	1.29%	8	1.47%
Southwestern Mandarin	66	12.15%	69	12.71%
Zhongyuan Mandarin	25	4.60%	27	4.97%
Hakka	2	0.37%	6	1.10%
Min	33	6.08%	23	4.24%
Goetian (Wu-Chinese)	136	25.05%	146	26.89%
Gan dialect	7	1.29%	3	0.55%
Hui dialect	0	0.00%	1	0.18%
Jin dialect	10	1.84%	13	2.39%
Xiang dialect	19	3.50%	15	2.76%
Cantonese	69	12.71%	76	14.00%
Others	1	0.18%	6	1.10%
Total	543	100.00%	543	100.00%

Panel B: Distribution by industry

Sector	CSRC Group	No. of deals	%
Agriculture, forestry, livestock and fishing	A	13	2.95%
Mining	B	16	3.64%
Manufacturing	C	198	45.00%
Utilities	D	23	5.23%
Construction	E	13	2.95%
Transportation	F	7	1.59%
Communication, software and information technology services	G	33	7.50%
Wholesale and retail	H	42	9.55%
Real Estate	J	49	11.14%
Hotel and catering, hygienism and social work	K	23	5.23%
Culture, sports and entertainment	L	8	1.82%
Comprehensive	M	15	3.41%

Table 2
Linguistic distance between acquirers and targets.
This table provides the sample distribution based on the linguistic distance (*LD*) between the acquirer and the target as well as the mean and median 5-day *CAR* within each *LD* group. ***, **, * stand for statistical significance at the 1%, 5%, and 10% levels, respectively.

LD			*CAR* [−2, +2]	
	N	%	Mean	Median
0	249	45.86%	0.017***	0.007***
1	39	7.18%	0.014	0.005
2	80	14.73%	0.001	−0.0002
3	85	15.65%	0.026***	0.015***
4	38	7.00%	−0.006	0.002
5	52	9.58%	−0.019	−0.009**
Total	543	100.00%	0.011***	0.004**

language frictions. However, the number of deals does not decrease monotonically as the linguistic distance between the acquirers and the targets increases, which suggests that other variables in addition to the language gap play a role in a firm's acquisition decision. Generally, in the remaining 54% of the deals in which the acquirers and the targets are from two different dialect language areas, 22% of the total samples have a relatively low gap (i.e., distance = 1 or 2), 16% have a median gap (i.e., distance = 3), and 16% have a high gap (distance = 4 or 5).

2.3. Model specification

To test whether linguistic distance affects acquisition outcome as predicted, we use the following regression model:

$$CAR_i = \alpha_0 + \alpha_1 * LDi + \Sigma\beta_j * Acquirer\ Characteristics_{i,j} + \Sigma\gamma_j * Deal\ Characteristics_{i,j} + \varepsilon_i \tag{1}$$

The dependent variable is the acquirer's 5-day cumulative abnormal return (*CAR*) around the acquisition announcement date. The event window used is [−2, +2], in which event day 0 is the acquisition announcement date and the estimation window is [−240, −41]. The abnormal return is estimated based on the CAPM model.

Following prior studies (e.g., Moeller et al., 2004, and Masulis et al., 2007), we control for a number of acquirer and deal characteristics. The deal-level variables include relative deal size, the method of payment (whether involving stock payment), whether the acquirer and the target are from the same industry, and whether the deal occurs in the high-tech industries defined in the CSRC guidelines.[6] The acquirer's characteristics comprise the size of the firm, the financial leverage, and Tobin's Q, all of which are measured at the most recent fiscal year end prior to the announcement date. Appendix A presents the definitions of each variable in detail. All the regressions control for announcement year fixed effect and the acquirer's industry fixed effect.

In addition to the control variables in the literature, we include the geographic distance (*GD*) between the acquirer and the target as a control variable. Uysal et al. (2008) document that the acquirer's return is negatively related to the geographic distance between the acquirer and the target due to the increases in information asymmetry and valuation difficulty of the target for far away targets. Other studies also suggest that geography matters (e.g., Butler, 2008; Kang and Kim, 2008, and Malloy, 2005). Moreover, by accounting for *GD*, we do not mix the impact of the linguistic distance with geographic distance. We measure the geographic distance as the logarithm of one plus the physical distance (in kilometers) of two cities in which the acquirer and the target are located.

Moreover, we include a set of institutional characteristic variables that are widely used in Chinese studies. For example, we consider regional GDP by province where the acquirer is located (*GDP*) as well as the regional difference in marketization (*MD*) between the acquirer's and the target's province by applying the index developed by Fan et al. (2010). The marketization index accounts for the differences in legal and social development in different Chinese provinces.

Table 3 presents the descriptive statistics of the 5-day *CAR* and *LD* and all the control variables. The average *LD* is 1.60 with a standard deviation of 1.75. Although almost 46% of the deals occur between two firms that speak the same dialect language, there is no clear clue on the distribution of the rest. Linguistic distance appears diverse when the acquirer and the target speak different languages.

The mean value of the 5-day *CAR* is 0.011. Because the targets in our sample are all private firms, it is not surprising that the acquirer's announcement return is positive. The 5-day *CAR* also shows large variation, with −0.028 at quartile and 0.035 at third quartile.

In terms of deal characteristics, the average relative deal size is 0.070 while the third quartile is 0.034, which indicates very few extremely large deals in our sample. Twenty percent of the deals involve stock payment, which is comparable to those documented in the literature. On average, 42% of the deals are from firms that operate in different industries while 29% of them are deals occurring in the high-tech industries.

An average acquirer has a firm size of 21.53 in natural logarithm (approximately RMB 2.24 billion), a financial leverage ratio of 0.507, and a Tobin's Q of 2.9. An average 0.507 financial leverage ratio seems higher than that of a typical acquirer in the US market. These characteristics suggest that acquirers in the Chinese M&A market are those firms that are large, have high market valuation, and use debt.

Table 4 reports the paired Pearson correlation coefficients of all the variables. It is interesting that the correlation between the linguistic distance and geographic distance is as high as 0.78. Hence, we control for the geographic distance in our analysis and provide a mitigation of the potential multicollinearity as a robust check.

3. Empirical results

3.1. Linguistic distance and acquirer's return

Panel A of Table 5 presents the results of Eq. (1). We include the year fixed effect and acquirer's industry fixed effect in all models. After controlling for the standard deal-level and acquirer-level variables that are widely used in the literature, the coefficient on the linguistic distance is negative and significant at the 1% level as shown in column (1), indicating that the linguistic distance between the acquirer and the target has an additional explanatory power in the cross-sectional difference in the merger outcome in addition to those documented in the literature. Based on column (1), if the linguistic distance increases by 1 level, which means the communication difficulty between two parties is higher by 1 level, the acquirer's merger return is reduced by 0.6%, suggesting that larger linguistic distance deals are favored less by the acquirer's shareholders. To obtain insight into the economic significance of *LD* on acquirer announcement returns and that of other factors already identified in previous studies affecting acquirer announcement

[6] According to the CSRC guidelines, high-tech industries include both R&D intensive manufacturing industries (6 categories) and service industries (9 categories). High-tech manufacturing industries include pharmaceutical manufacturing, aerospace equipment manufacturing, electric and communication equipment manufacturing, computer and office equipment manufacturing, pharmaceutical instrumentation manufacturing, and photographic equipment manufacturing industries. High-tech service industries include information service, e-business service, research and design service, technology development service, intellectual property right service, environment governance, and others.

Table 3
Summary statistics.
This table comprises 543 domestic M&As in Mainland China announced between 2000 and 2012. It describes the mean, median, standard deviation, and 25% and 75% of all the variables. Variable definitions are in Appendix A.

	Mean	Std. dev.	25%	Median	75%
LD	1.595	1.745	0	1	3
CAR[−2, +2]	0.011	0.068	−0.028	0.004	0.035
Deal characteristics:					
DEALSIZE	0.070	0.320	0.004	0.012	0.034
PAYMENTSTOCK	0.020	0.141	0	0	1
DIVERSIFYING	0.418	0.494	0	0	1
HIGHTECH	0.291	0.455	0	0	1
Acquirer characteristics:					
SIZE	21.53	1.271	20.663	21.368	22.215
LEVERAGE	0.507	0.818	0.316	0.502	0.622
TQ	2.902	5.962	1.401	2.098	3.323
Institutional characteristics:					
MD (Acquirer)	0.856	1.112	0	0.25	1.41
GDP (Acquirer)	4.139	0.402	3.886	4.177	4.430
Geographic characteristic:					
GD	2.038	1.352	0.000	2.63	3.12
CEO characteristics:					
POLITICAL	0.495	0.500	0	0	1
DUAL	0.192	0.394	0	0	0
TENURE	3.927	2.827	1.89	3.2	5.46
AGE	49.917	7.290	45	49	55
EDUCATION	3.444	0.855	3	4	4

Table 4
Correlation coefficients.
This table reports the paired Pearson correlation coefficients. p-values are in Italics. Variable definitions are in Appendix A. Figures in bold mean significance at the 5% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
LD (1)	1										
SIZE (2)	**0.097**	1									
	0.022										
LEVERAGE (3)	0.025	−0.023	1								
	0.550	*0.589*									
TQ (4)	−0.055	**−0.277**	**0.094**	1							
	0.192	*0.000*	*0.026*								
DEALSIZE (5)	0.083	**−0.113**	**0.225**	0.058	1						
	0.050	*0.007*	*0.000*	*0.167*							
DIVERSIFYING (6)	−0.040	**−0.084**	0.060	0.030	−0.019	1					
	0.347	*0.047*	*0.154*	*0.475*	*0.650*						
PAYMENTSTOCK (7)	−0.031	**−0.128**	**0.242**	0.025	**0.092**	−0.007	1				
	0.461	*0.002*	*0.000*	*0.558*	*0.030*	*0.873*					
HIGHTECH (8)	−0.008	**−0.140**	**−0.092**	−0.027	−0.039	**−0.212**	−0.007	1			
	0.859	*0.001*	*0.030*	*0.522*	*0.359*	*0.000*	*0.871*				
GDP (9)	−0.014	**0.157**	−0.042	0.053	0.017	**−0.092**	0.002	**0.159**	1		
	0.749	*0.000*	*0.321*	*0.213*	*0.695*	*0.029*	*0.957*	*0.000*			
GD (10)	**0.728**	**0.098**	0.028	−0.058	0.050	−0.068	−0.021	0.014	0.026	1	
	0.000	*0.020*	*0.512*	*0.166*	*0.235*	*0.106*	*0.615*	*0.737*	*0.538*		
MD (11)	**0.603**	0.045	−0.010	−0.027	**0.089**	−0.041	−0.035	0.034	0.033	**0.591**	1
	0.000	*0.290*	*0.821*	*0.519*	*0.035*	*0.336*	*0.407*	*0.415*	*0.439*	*0.000*	
CAR [−2, +2]	−0.106	−0.038	−0.019	−0.027	−0.011	−0.014	**0.238**	0.013	−0.018	−0.050	−0.017
	0.012	*0.374*	*0.656*	*0.522*	*0.791*	*0.734*	*0.000*	*0.750*	*0.663*	*0.241*	*0.683*

returns, we report the percent change of *CAR* to one standard deviation change in these variables in Panel B of Table 5. As reported, one standard deviation increase in *LD* will decrease the announcement return by 1.05 percentage point. Common variables that have higher economic significance on acquirer return are the method of payment (i.e., a dummy variable for whether paying in stock). Other commonly used variables that have comparable economic significance include relative deal size and leverage. Such comparison means linguistic distance is not a trivial variable to the M&As.

Concerning the high correlation between the linguistic distance and geographic distance as shown in Table 4, we run the regressions in column (2) of Table 5 with the log form of the distance between the acquirer's headquarters and the target's headquarters.

Table 5

The impact of linguistic distance on acquirers' cumulative abnormal return.

Panel A of Table 5 reports the OLS regression results of 5-day acquirer's CAR around the announcements of 543 domestic M&A in Mainland China. *LD* is the linguistic distance between the acquirer and the target. The definitions of other control variables are in Appendix A. All the columns control for acquirer's industry and announcement year. In parentheses are two-sided p-values based on standard errors adjusted for heteroskedasticity (White, 1980) and acquirer clustering (Petersen, 2009). Panel B shows the results of comparing one standard deviation change in *LD* with that of other factors in Panel A column (3). ***, **, * stand for statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Regression results

	(1)	(2)	(3)
LD	−0.006***	−0.009***	−0.010***
	(0.001)	(0.002)	(0.002)
DEALSIZE	0.030	0.030	0.029
	(0.153)	(0.153)	(0.172)
PAYMENTSTOCK	0.097***	0.099***	0.101***
	(0.005)	(0.004)	(0.003)
DIVERSIFYING	−0.004	−0.004	−0.004
	(0.469)	(0.515)	(0.525)
HIGHTECH	−0.002	−0.002	−0.002
	(0.738)	(0.719)	(0.691)
SIZE	−0.0003	−0.0002	−0.0001
	(0.896)	(0.929)	(0.975)
LEVERAGE	−0.012***	−0.012***	−0.011***
	(0.001)	(0.001)	(0.001)
TQ	−0.001**	−0.001*	−0.001*
	(0.046)	(0.060)	(0.067)
GDP	−0.018*	−0.018*	−0.017*
	(0.070)	(0.078)	(0.084)
GD		0.004	0.003
		(0.186)	(0.309)
MD			0.004
			(0.201)
Industry	YES	YES	YES
Year	YES	YES	YES
Constants	0.121*	0.111	0.106
	(0.090)	(0.123)	(0.143)
N	543	543	543
R-Squared	0.119	0.122	0.125

Panel B: Economic significance of LD using column (3) of Panel A

Factors (X) contributing to acquirer's announcement return	Coefficients in column (3) of Panel A	Standard deviation of the factors	ΔCAR (in %) to 1 standard deviation in X
LD	−0.006***	1.745	1.05
DEALSIZE	0.029	0.320	0.93
PAYMENTSTOCK (Dummy)	0.101***	0.141	10.1
DIVERSIFYING (Dummy)	−0.004	0.494	0.40
SIZE	−0.0001	1.271	0.13
LEVERAGE	−0.011***	0.818	0.90
TQ	−0.001*	5.962	0.60
GDP	−0.017*	0.402	0.68

We find that the negative relationship between the acquirer's return and the linguistic distance still holds after controlling for the geographic distance between the acquirer and the target. This mitigates our concern that the effect of linguistic distance is driven by the difference in geography. Prior studies find that geographical proximity may reduce the information asymmetry through local presence and networking (Butler, 2008 and Malloy, 2005), and therefore, a closer geographical proximity is expected to help the acquirer identify a suitable target, avoid overpaying, facilitate the transaction process and smooth the realization of the synergy gains. Interestingly, the correlation between *CAR* and the *GD* is negative and insignificant in Table 4 and when we include it in the regressions. The coefficient of *GD* is still insignificant, which may indicate that location does not matter in M&A decisions. More importantly, linguistic distance plays a role in explaining the cross-sectional difference in merger performance beyond the location distance.

Regional difference in marketization (*MD*) is another concern caused by our measurement of linguistic distance. Because assigning language area is based on the location where the firm operates, the linguistic distance may also capture the difference in the regional economics that may affect the acquisition outcome. We control for the difference in the regional economics using the marketization index developed by Fan et al. (2010). In column (3), we find that the *MD* variable is negative albeit insignificant with the acquirer's abnormal return. After controlling for the marketization distance, the linguistic distance variable is still significantly negatively correlated with the acquisition performance.

To further alleviate the concern of collinearity between the *LD* and *GD* variables, we use. two approaches to address this issue. First, we replace the *LD* with the residual from the regression of *LD* on *GD* (Step 1). By construction, the residual should have zero correlation with *GD*, i.e., the part of *LD* that is not related to *GD*. We then include both the residual and *GD* in the regression of announcement return (Step 2). Second, we conduct an orthogonal transformation of both *LD* and *GD* and use the transformed variables in the regression equation. The results are presented in Appendix C. In Panel A of Appendix C, the coefficients of the *GD* turn significant and residual is still significantly negatively related to announcement return. In Panel B of Appendix C, both transformed *LD* and *GD* are negative and significant at the 5% level. The results in both panels indicate that the significant sign of *LD* is not driven by its collinearity with *GD*, which should be negatively related to announcement return.

3.2. The effect of linguistic distance: cross-sectional variation

Thus far, we have documented a robust negative relationship between the market reaction measured as the acquirer's abnormal return around the acquisition announcement and the linguistic distance between the acquirer and the target, supporting our hypothesis. In this section, we explore whether the negative effect of linguistic distance displays any cross-sectional variations.

To test our assumptions, we separate the sample into three subsamples based on (1) whether the deal is a high-tech merger; (2) Geographic differences in Putonghua Proficiency; (3) Geographic differences in Dialect diversity.

3.2.1. High-tech vs. non-high-tech mergers and acquisitions

Technology makes few ambiguous arguments. If a merger is undertaken between two high-tech firms, either the management or the employees communicate with each other using technology words, in a concise and clear way. Thus, high-tech mergers are less influenced by the cultural difference. We test this conjecture by dividing the sample between deals that occur between two high-tech firms and those that do not. We expect to find that the effect of linguistic distance, one aspect of the cultural difference, should be weaker in the high-tech deals.

Table 6

Cross-sectional variations on the effect of linguistic distance.

This table reports the OLS regression results of 5-day acquirer's CAR within each subsample. Column (1) includes only deals from high-tech industries, and column (2) includes non-high-tech deals. Column 3 includes the acquirers from high Putonghua popularity areas and column (4) includes the acquirers from low Putonghua popularity areas. Column (5) includes the acquirers from language low diversity areas and column (6) includes the acquirers from language high diversity areas. *LD* is the linguistic distance between the acquirer and the target. The definitions of other control variables are in Appendix A. All the columns control for acquirer's industry and announcement year fixed effect. In parentheses are two-sided p-values based on standard errors adjusted for heteroskedasticity (White, 1980) and acquirer clustering (Petersen, 2009). ***, **, * stand for statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Hightech = 1	Hightech = 0	High popularity	Low popularity	High diversity	Low diversity
LD	−0.005	−0.011***	−0.008	−0.009**	−0.004	−0.015***
	(0.306)	(0.005)	(0.166)	(0.025)	(0.347)	(0.006)
DEALSIZE	0.075**	0.024	0.016	0.037	0.093**	0.009
	(0.027)	(0.263)	(0.120)	(0.307)	(0.043)	(0.619)
PAYMENTSTOCK	0.049	0.109**	0.172***	0.061*	0.049	0.112***
	(0.168)	(0.024)	(0.001)	(0.096)	(0.560)	(0.000)
DIVERSIFYING	−0.007	−0.004	−0.003	−0.005	0.006	−0.016
	(0.534)	(0.586)	(0.721)	(0.562)	(0.447)	(0.101)
HIGHTECH			−0.003	0.002	−0.003	−0.005
			(0.786)	(0.845)	(0.682)	(0.551)
SIZE	−0.003	0.001	−0.0005	−0.001	−0.002	0.0002
	(0.546)	(0.865)	(0.906)	(0.876)	(0.509)	(0.965)
LEVERAGE	0.044	−0.012***	0.026	−0.011**	−0.020***	0.024
	(0.114)	(0.004)	(0.401)	(0.026)	(0.000)	(0.309)
TQ	0.003	−0.001*	0.002	−0.001	−0.004	−0.0001
	(0.351)	(0.079)	(0.737)	(0.150)	(0.166)	(0.844)
GDP	−0.031*	−0.013	0.028	−0.026**	−0.017	−0.020
	(0.090)	(0.284)	(0.237)	(0.022)	(0.232)	(0.199)
GD	0.003	0.003	0.005	0.001	0.004	0.003
	(0.546)	(0.433)	(0.370)	(0.748)	(0.289)	(0.631)
MD	−0.004	0.007	−0.001	0.005	−0.004	0.011**
	(0.537)	(0.106)	(0.916)	(0.229)	(0.352)	(0.023)
Year	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES
Constant	0.196	0.076	−0.102	0.157	0.163	0.102
	(0.178)	(0.382)	(0.514)	(0.110)	(0.135)	(0.319)
N	158	385	218	325	319	224
R-Squared	0.281	0.108	0.203	0.129	0.180	0.189

Columns (1) and (2) of Table 6 present the regression results for high-tech deals and non-high-tech deals, respectively. All the control variables are the same as those in column (3) of Table 5. We find that the linguistic distance measure is only significant for the deals in which the acquirer and the targets are not both from high-tech industries. Moreover, the coefficient is more negative for the non-high-tech deals, suggesting that indeed, the language friction plays a greater role in industries such as manufacturers and retailers.

3.2.2. Promotion of Putonghua in China

Promotion of Putonghua has been a movement led by the government of China since the 1980s. Researchers may argue that linguistic distance no longer matters, as two parties can communicate with each other using Putonghua as a common dialect in the acquisition process. However, using a sample of acquisitions starting from 2000, 20 years after the initiation of the Putonghua Promotion movement, we still find a significantly negative relationship between the linguistic distance and acquirer's return. In fact, in the Survey of Language Situation in China done by State Language Commission in, 2006, only 53.06% of the population is proficient in Putonghua and only 41.97% of the population speaks Putonghua in the working environment. The survey says that, major reasons that prevent people speaking Putonghua include lack of a rich Putonghua language environment and difficulty to change local accent (or “Xiangyin”, see Dai et al., 2016). The popularity of Putonghua varies much by regions. Putonghua is most popular in Beijing (90.36%) and least popular in Qinghai (31.43%) according to the Survey. Therefore, we hypothesize that acquirers from areas where Putonghua is less popular suffer more from the potential language frictions in the negotiation process than those from Putonghua more popular areas.

Columns (3) and (4) in Table 6 test our conjecture. We separate the acquirers located in cities or provinces with a Putonghua proficiency rate above 53.06% from those in the cities or provinces with the rate below 53.06%. The coefficients on the linguistic distance measure are negative for both subsamples, but only statistically significant for the acquirers from Putonghua less popular areas and with a slightly larger magnitude.

3.2.3. The effect of linguistic diversity in China

It is well known that China is one of the most linguistically diverse countries in the world, and such linguistic diversity is caused by its geographic origins. It is observed that people living in the north of China, including provinces such as Beijing, Shandong, and Liaoning use the same language while people living in the south of China, including provinces such as Fujian and Zhejiang have other languages developed. If language carries frictions in the acquisition process, is the acquirer from the north of China, where linguistic diversity is low more affected by the language barriers or the one from the south of China, where linguistic diversity is high?

Following Xu et al. (2015), we measure the linguistic diversity for each city as the number of local dialects[7] spoken in that city. On average, an acquirer is operating in a city within which six different local dialects are spoken. Chang et al. (2015) argue that people living in linguistically diverse areas just speak one of the many dialects, but they are aware of the diversity in languages and cultures. In other words, they may be more open to a new dialect environment and less shocked by the difference in languages and cultures. Thus, the acquirers from areas with a low level of dialect diversity perceive higher difficulty in communicating with the other party who speaks a different native language and are more affected by the linguistic distance between the two in the acquisition process than those from high dialect diversity area.

The acquirers are divided into two subsamples based on the linguistic diversity of the province in which it is located. Column (5) of Table 6 includes acquirers from provinces with low diversity and column (6) of Table includes acquirers from provinces with high diversity. The negative effect of linguistic distance is more pronounced for the acquirers from low diversity areas.

3.3. Robustness checks

3.3.1. Regional fixed effect

Since our key variable linguistic distance is measured based on acquirer and target's location, it is likely that this variable also captures the effects caused by location or region. Although we address this concern by adding the geographic distance between the acquirer and the target in previous regressions, it is still possible that some unmeasurable and/or unobservable regional characteristics may cause a variation in both the language and the market reaction during the acquisition announcement. To further control for the effects caused by region, we add acquirer's regional fixed effect in the main regression.[8] If two firms operate in the same province, we define them in the same region. Column (1) of Panel A in Table 7 presents the regression results. The coefficient of the linguistic distance measure is still negative and statistically significant.

3.3.2. Dialect language fixed effect

One possible concern of our main result is that the effect may come from the type of the language the firm belongs to rather than the difference in the language between two firms. For example, Cantonese is shown to be the most isolated dialect language, so for a Cantonese acquirer, the likelihood of larger distance is supposed to be high given the feature of Cantonese. If there is any observable

[7] Here local dialect means a sub-subsidiary of the dialect group defined in the Altas. For example, Hangzhou, a city in Zhejiang Province, belongs to the Taihu Lake Dialect subsidiary of the Goetian group. Within Hangzhou, the urban areas such as downtown belong to the Hangzhou sub-subsidiary while the rural areas such as Xiaoshan belong to the Linshao sub-subsidiary and Lin'an belongs to the Suhujia sub-subsidiary. Therefore, if you count the number of local dialects spoken in Hangzhou, it is 3.

[8] The result still holds if we control for the target's regional fixed effect.

Table 7
Robustness checks.

This table reports the OLS regression results of 5-day acquirer's CAR around the announcements of 543 domestic M&A in Mainland China. Panel A uses a fixed effect model. *LD* is the linguistic distance between the acquirer and the target. Panel B uses a dummy variable to capture the effect of linguistic distance. *LD_DUMMY* is a dummy that equals one if the acquirer and the target belong to different types of the dialect language and zero otherwise. Panel C constructs a series of dummy variables that account for all 6 different levels of linguistic distance. *LD_i* is a dummy that equals one if the linguistic distance between the acquirer and the target is i, where i is from 0 to 5. The definitions of other control variables are in Appendix A. All the columns control for acquirer's industry and announcement year fixed effect. In parentheses are two-sided p-values based on standard errors adjusted for heteroskedasticity (White, 1980) and acquirer clustering (Petersen, 2009). ***, **, * stand for statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Acquirer's region/language fixed effect

	(1)	(2)
LD	−0.010***	−0.010***
	(0.003)	(0.001)
DEALSIZE	0.033	0.030
	(0.134)	(0.160)
PAYMENTSTOCK	0.097***	0.102***
	(0.008)	(0.003)
DIVERSIFYING	−0.006	−0.004
	(0.360)	(0.505)
HIGHTECH	−0.001	−0.001
	(0.937)	(0.890)
SIZE	−0.0005	−0.0004
	(0.864)	(0.880)
LEVERAGE	−0.014***	−0.012***
	(0.000)	(0.001)
TQ	−0.001**	−0.001*
	(0.044)	(0.056)
GDP	0.164	−0.011
	(0.154)	(0.389)
GD	0.003	0.004
	(0.486)	(0.277)
MD	0.005	0.005
	(0.199)	(0.134)
Industry	YES	YES
Language type		YES
Region	YES	
Year	YES	YES
Constant	−0.367	0.121
	(0.262)	(0.120)
N	543	543
R-Squared	0.176	0.139

Panel B: A dummy approach to measure LD

	(1)	(2)	(3)
LD_DUMMY	−0.015**	−0.018*	−0.019*
	(0.016)	(0.089)	(0.080)
DEAL SIZE	0.028	0.028	0.027
	(0.193)	(0.198)	(0.209)
PAYMENTSTOCK	0.097***	0.098***	0.098***
	(0.007)	(0.007)	(0.006)
DIVERSIFYING	−0.005	−0.005	−0.005
	(0.431)	(0.429)	(0.428)
HIGHTECH	−0.002	−0.002	−0.002
	(0.724)	(0.714)	(0.703)
SIZE	−0.001	−0.001	−0.001
	(0.740)	(0.741)	(0.751)
LEVERAGE	−0.011***	−0.011***	−0.011***
	(0.002)	(0.003)	(0.003)
TQ	−0.001*	−0.001*	−0.001*
	(0.064)	(0.071)	(0.075)
GDP	−0.017	−0.016	−0.016
	(0.104)	(0.108)	(0.112)
GD		0.002	0.001
		(0.673)	(0.773)

(continued on next page)

Table 7 (*continued*)

Panel B: A dummy approach to measure LD

	(1)	(2)	(3)
MD			0.002
			(0.583)
Industry	YES	YES	YES
Year	YES	YES	YES
Constants	0.122*	0.119	0.117
	(0.093)	(0.103)	(0.109)
N	543	543	543
R-Squared	0.107	0.107	0.108

Panel C: A monotonic relationship

	(1)	(2)	(3)
LD_1	−0.006	−0.011	−0.012
	(0.536)	(0.368)	(0.361)
LD_2	−0.017**	−0.022**	−0.025**
	(0.018)	(0.041)	(0.027)
LD_3	0.006	−0.0004	−0.004
	(0.473)	(0.973)	(0.788)
LD_4	−0.025***	−0.032**	−0.036**
	(0.006)	(0.016)	(0.011)
LD_5	−0.046***	−0.054***	−0.058***
	(0.000)	(0.001)	(0.001)
DEALSIZE	0.031	0.031	0.029
	(0.131)	(0.134)	(0.150)
PAYMENTSTOCK	0.098***	0.100***	0.101***
	(0.003)	(0.003)	(0.002)
DIVERSIFYING	−0.004	−0.004	−0.004
	(0.489)	(0.492)	(0.497)
HIGHTECH	−0.004	−0.005	−0.005
	(0.481)	(0.470)	(0.452)
SIZE	−0.0002	−0.0002	−0.0001
	(0.917)	(0.929)	(0.962)
LEVERAGE	−0.012***	−0.012***	−0.012***
	(0.000)	(0.000)	(0.001)
TQ	−0.001**	−0.001**	−0.001*
	(0.037)	(0.045)	(0.051)
GDP	−0.018*	−0.018	−0.017
	(0.072)	(0.078)	(0.083)
GD		0.003	0.002
		(0.455)	(0.588)
MD			0.004
			(0.256)
Industry	YES	YES	YES
Year	YES	YES	YES
Constant	0.118*	0.113	0.109
	(0.092)	(0.111)	(0.125)
N	543	543	543
R-squared	0.144	0.145	0.147

variable that makes Cantonese firms more likely to conduct a bad acquisition, then the negative relationship between linguistic distance and acquirer return is spurious. Therefore, we add an acquirer's language fixed effect to address this issue.[9] Column (2) of Panel B in Table 7 presents the regression result after controlling for the acquirer's language types. The negative effect of the linguistic distance still holds.

3.3.3. *A dummy variable approach*

So far, the language difference between the acquirer and target has been measured in levels. In this section, we apply a dummy approach for a robustness check. Like including a common language dummy variable in most studies, we create a dummy variable for *LD* (*LD_DUMMY*) that separates those deals in which the acquirer and the target are in the same language areas from those they are in different language areas. *LD_DUMMY* equals zero if the acquirer and the target speak the same dialect, and one otherwise. The results are presented in Panel B of Table 7. The coefficients of *LD_ DUMMY* are negative and significant at the 5% and 10% levels in columns

[9] The result still holds if we control for the target's language type fixed effect.

(1) and (3), respectively. The findings offer some support for our argument.

3.3.4. A monotonic relationship?

Our unique measure of linguistic distance provides an opportunity to test whether there is a monotonic decreasing relationship between linguistic distance and acquirer return. Although statistics in Table 2 suggest an ambiguously monotonic relationship, a regression with control variables can provide more direct evidence. Therefore, in Panel C of Table 7, we construct a series of dummy variables that account for all six different levels of linguistic distance and re-run the main regressions by including five of them. *LD_i* is a dummy variable that equals one if the linguistic distance between the acquirer and the target is defined as *i* in our sample, and zero otherwise, where *i* ranges from 0 to 5.

The regression result in column (3) shows that compared to the base level (i.e., where linguistic distance between the acquirer and the target is equal to 0), increasing the linguistic distance by 1, 2, 3, 4, and 5 reduces the acquirer return by 1.2%, 2.5%, 0.4%, 3.6%, and 5.8%, respectively. Generally, it suggests a monotonic decreasing relationship between the linguistic distance and the acquirer return although there is a jump when the linguistic distance equals 3. Although almost half of the firms speak the same dialect while the other half speak different dialects as their targets, we can argue that our results are not mainly driven by such binary features. The distance in level matters too. Using our linguistic distance measure extends the findings of previous studies that only focus on a binary definition of language difference.

3.4. Additional analyses

3.4.1. Does CEO's language experience account for the impact of linguistic distance on M&A CAR?

Our analysis so far suggests that linguistic distance, a proxy of cultural friction, reduces the value of acquisitions to the acquirer's shareholders. Prior studies document that CEO's personality and experience matter in corporate decisions (Kaplan et al., 2012 and Benmelech and Frydman, 2015). It is interesting to investigate whether CEO's prior language experience affects merger and acquisition outcome in this context.

We construct several variables related to the acquirer's CEO language experience. If the CEO's place of origin is disclosed, we determine their language background based on the place of origin. If the information on the place of origin is not available, we use their previous and current working locations. For those CEOs who have been working in several different places, we consider the one with the longest working time. A dummy variable is used to examine whether the CEO has ever been exposed to the dialect of the area in which the target is located (*CEO_EXPERIENCE*). We also measure the linguistic distance between the CEO and the target firm (*CEO_LD*) based on the CEO's language experience determined in the above way.

We regress these measures on the acquirer's 5-day CAR with other firm-level, deal-level and CEO-level control variables. Columns (1) to (2) of Table 8 show the regression results with the CEO's various language experience measures. We find that the coefficient of *CEO_EXPERIENCE* is positive and significant at the 5% level while that of *CEO_LD* is negative and significant at the 1% level. The results suggest that: (1) the dialect or the culture of the acquirer's CEO learned in his working places helps the acquirer understand the deal and smoothly integrate with the target, and (2) the linguistic distance significantly reduces the value of acquisition only if the acquirer's CEO was born in a dialect area other than that of the target firm.

3.4.2. The validity of the transmission channels

Our empirical findings have two underlying channels: (1) linguistic background facilitates communication between the bidder and target at the time of deal negotiation, and (2) a similar linguistic background facilitates post-merger coordination/integration between the employees of each firm.[10]

If the first channel is valid, we expect that if the acquirer hires an investment bank to provide M&A advisory services, the investment bank will negotiate with the target on the valuation, and the negative effect of language barriers between the acquirer and the target would be less severe, as the investment bank facilitates communication between them. Thus, we collect the information on the acquirer's investment bank and create a dummy variable on whether the acquirer hires an investment bank as financial advisor in the deal (*ADVISOR*). We interact *ADVISOR* with our linguistic distance variable (*LD*) in Eq. (1) and run the main regression with this new variable. We expect that the coefficient on this new variable should be positive, as including an investment bank reduces the negative effect caused by linguistic distance.

Following Li et al. (2017), we find 327 of 543 deals that have available information on investment banks. The missing data is caused by (1) some of the investment banks did not disclose the company's name it served; (2) data on some deals are not available prior to 2009, as the investment bank's M&A advisory service has not been specified by the government since late 2008. Among 327 deals, 63% hired investment banks as financial advisors for the deal. Table 9 presents the results controlling for investment bank hiring. Whether an investment bank is involved in a deal does not affect the deal outcome significantly in our sample (i.e., the coefficient of *ADVISOR* is positive but not statistically significant), but it does mitigate the negative effect of the linguistic distance in a significant way. For deals without an investment bank involved, one level of *LD* increase results in a 1.6% *CAR* decrease. While for deals with an investment bank involved, the *CAR* decreasing is only 0.4% (i.e., 1.6% – 1.2%). In other words, hiring an investment bank will reduce the *CAR* decrease caused by linguistic distance by 1.2%, which is economically significant. Therefore, the empirical result indicates that the linguistic factor plays a part during the deal negotiation between the acquirer and the target. However, hiring

[10] We acknowledge an anonymous reviewer in raising the suggestions.

Table 8
The impact of CEO experience and personal linguistic characteristics.

This table reports the OLS regression results of 5-day acquirer's CAR. *CEO_EXPERIENCE* is a dummy that equals one if the acquirer CEO's place of origin or previous or current working location speaks the same dialect as in the target firm's location. *CEO_LD* measures linguistic distance between acquirer CEO and the target. The definitions of other control variables are in Appendix A. Both columns control for acquirer's industry and announcement year fixed effect. In parentheses are two-sided p-values based on standard errors adjusted for heteroskedasticity (White (1980)) and acquirer clustering (Petersen (2009)). ***, **, * stand for statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
CEO_EXPERIENCE	0.014**	
	(0.013)	
CEO_LD		−0.005***
		(0.003)
CEO characteristics:		
POLITICAL	−0.005	−0.004
	(0.445)	(0.502)
DUAL	−0.006	−0.005
	(0.434)	(0.471)
TENURE	−0.001	−0.0005
	(0.586)	(0.639)
AGE	0.0001	−0.00004
	(0.911)	(0.920)
EDUCATION	0.004	0.004
	(0.232)	(0.228)
Deal characteristics:		
DEALSIZE	0.028	0.029
	(0.194)	(0.169)
PAYMENTSTOCK	0.094**	0.100***
	(0.011)	(0.005)
DIVERSIFYING	−0.004	−0.004
	(0.516)	(0.547)
HIGHTECH	−0.002	−0.002
	(0.735)	(0.736)
Acquirer characteristics:		
SIZE	−0.001	−0.0002
	(0.798)	(0.926)
LEVERAGE	−0.011***	−0.012***
	(0.002)	(0.001)
TQ	−0.0005	−0.001*
	(0.121)	(0.054)
Regional characteristics:		
GDP	−0.014	−0.014
	(0.180)	(0.184)
Industry	Yes	Yes
Year	Yes	Yes
Constant	0.078	0.089
	(0.287)	(0.221)
N	543	543
R-Squared	0.112	0.117

a third party to facilitate the communication could mitigate the concerns caused by linguistic distance between the acquirer and the target.

For the validity of the second channel, we consider the post-merger integration cost and the culture clash. For the post-merger integration cost, we consider that it is higher when the relative deal size is larger or when the target is from a different industry than the acquirer. Therefore, we use a dummy variable (*REL_DEAL_SIZE*) that equals one for deals in the top 30 percentile of relative deal size and zero for deals in the bottom 30 percentile of relative deal size as well as another dummy variable for diversifying deals (*DIVERSIFYING = 1* if an acquirer and the target are from different industries, and zero otherwise) as proxies of the post-merger integration cost (*COST_PROXY*) and interact them with our linguistic distance measure (*LD*), respectively, in Eq. (1) and examine whether a similar linguistic background is more appreciated when the post-merger integration cost is higher.

Table 10 presents the findings on how linguistic background may affect the deal outcome through post-merger integrations. In column (1) of Table 10, we compare deals in the top 30 percentile of relative deal size with those in the bottom 30 percentile. Although the median value of *REL_DEAL_SIZE* for the entire sample is 1.2%, it varies greatly. An average deal in the top 30 percentile has the target size as large as 21% of the acquirer while an average deal in the bottom 30 percentile has a relative size of 0.2%. The

Table 9
The impact of hiring an investment advisor.

This table reports the OLS regression results of the impact of hiring an investment advisor on the 5-day acquirer's CAR. *ADVISOR* is a dummy variable if the deal has an investment bank as an advisor, *ADVISOR* = 1 and zero otherwise. The definitions of other control variables are in Appendix A. Both columns control for acquirer's industry and announcement year fixed effect. In parentheses are two-sided p-values based on standard errors adjusted for heteroskedasticity (White, 1980) and acquirer clustering (Petersen, 2009). ***, **, * stand for statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = CAR
LD × ADVISOR	0.012***
	(0.008)
LD	−0.016***
	(0.001)
ADVISOR	−0.009
	(0.423)
DEALSIZE	0.011
	(0.566)
PAYMENTSTOCK	0.089**
	(0.048)
DIVERSIFYING	0.005
	(0.568)
HIGHTECH	−0.006
	(0.468)
SIZE	0.003
	(0.339)
LEVERAGE	−0.008**
	(0.021)
TQ	−0.0003
	(0.320)
GDP	−0.022*
	(0.082)
GD	0.004
	(0.381)
MD	0.006
	(0.218)
Industry	YES
Year	YES
Constant	0.055
	(0.565)
N	327
R-Squared	0.139

interaction term (*LD* × *COST_PROXY*) in column (1) is negative and statistically significant at the 5% level. However, the linguistic distance measure becomes insignificant, suggesting that the linguistic distance plays a role only when the relative deal size is large. In column (2), we find that the linguistic distance is negatively related to announcement return and the negative effect is more pronounced in diversifying deals. Overall, we find some evidence that the linguistic background plays a role in the post-merger integrations of the mergers and acquisitions.

For culture clash, it is well known that it is a key reason for the failure of many mergers and acquisitions. On the one hand, culture differences have a large impact on mergers (Ahern et al., 2015). On the other hand, how a company values the culture and builds the corporate culture may play a role in the coordination with others. For example, to integrate a company with a short history and weak culture background would be easier than to integrate a company with a long history and with strong culture value, other things being equal. Therefore, the higher is the culture strength of the targets, the higher is the post-merger integration cost that is expected for the acquirers.

To construct the culture strength variable (*CULTURE_STRENGTH)*, we count Wang and Kan's (2014) five indicators from three aspects – company, employee, and social media. If the target firm introduces its corporate culture on its website, we count 1. If it introduces corporate mission on its website, we count 1. If the company has employee handbook with cultures of value, we count 1. If the company has ever trained their employees in cultures of value, we count 1. If the company has ever advertised its cultures in any social media, we count 1. The culture strength index is the sum of the five indicators. In our sample, *CULTURE_STRENGTH* of the targets varies from 0 to 5, with a mean value of 2.95. We include *LD*, *CULTURE_STRENGTH,* and an interaction term in the regression. In Table 11, the coefficients on

Table 10
The impact of relative deal size and diversifying deals.

This table reports the OLS regression results of the impact of relative deal size and diversifying deals 5-day acquirer's CAR. We use the relative deal size in the top 30 and bottom 30 percentile in column (1). *REL_DEAL_SIZE* = 1 if the relative deal size is in the top 30 percentile and zero if in the bottom 30 percentile of the entire sample. For diversifying deals, *DIVERSIFYING = 1* if the acquirer and target are from different industry and zero otherwise. *REAL_DEAL_SIZE* and *DIVERSIFYING* are proxies of post-merger integration cost (*COST_PROXY*). The definitions of other control variables are in Appendix A. Both columns control for acquirer's industry and announcement year fixed effect. In parentheses are two-sided p-values based on standard errors adjusted for heteroskedasticity (White, 1980) and acquirer clustering (Petersen, 2009). ***, **, * stand for statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Relative deal size	(2) Diversifying deal
LD × COST_PROXY	−0.009**	−0.007*
	(0.041)	(0.054)
LD	−0.007	−0.007**
	(0.131)	(0.026)
COST_PROXY	0.025*	0.006
	(0.058)	(0.436)
DEALSIZE		0.032
		(0.130)
DIVERSIFYING	−0.002	
	(0.794)	
PAYMENTSTOCK	0.117***	0.099***
	(0.008)	(0.003)
HIGHTECH	−0.004	−0.002
	(0.634)	(0.701)
SIZE	−0.005	0.0004
	(0.146)	(0.883)
LEVERAGE	−0.008***	−0.012***
	(0.007)	(0.001)
TQ	−0.001**	−0.001*
	(0.013)	(0.051)
GDP	−0.025*	−0.017*
	(0.065)	(0.076)
GD	0.006	0.003
	(0.243)	(0.316)
MD	0.001	0.005
	(0.766)	(0.169)
Industry	YES	YES
Year	YES	YES
Constant	0.233**	0.092
	(0.020)	(0.203)
N	321	543
R-Squared	0.184	0.132

LD and *CULTURE_STRENGTH* are both negative albeit insignificant. The interaction term is negative and significant at the 10% level, suggesting that a strong target cultural strength amplifying the negative impact of the linguistic distance on *CAR*.

3.4.3. The impact of director social connection

When the acquirer and the target speak similar language areas, top management from both firms may know each other well as they may work together now or have done so before, have gone to the same college before or be involved in the same club or local organization now or before. Thus, lower linguistic distance may be related to potential social connections between the acquirer and the target. Empirical studies document that social connections between the acquirer and the target have contributed to the announcement returns in mergers and acquisitions (Ishii and Xuan, 2014) and it is likely that the negative correlation between the linguistic distance and the market return is superficial and is driven by the social connections between the CEOs or directors between the two firms.

To address this concern, we construct a variable to control for potential social connections between two companies. If the acquirer has a director whose hometown is from the target's location, the acquirer may obtain valuable advice from this director's social connections in the local place. A dummy variable (*DIR_SC*) equals one if the acquirer has any director from the target's location, and zero otherwise. We examine whether the linguistic distance measure still has a significant effect on announcement return after controlling for acquirer director's social connection dummy variable (*DIR_SC*). In Table 12, the coefficient on *DIR_SC* is positive albeit

Table 11
The impact of target cultural strength.

This table reports the OLS regression results of the impact of target cultural strength on the 5-day acquirer's CAR. To construct the culture strength variable (*CULTURE_STRENGTH)*, we count Wang and Kan's (2014) five indicators from three aspects – company, employee, and social media. If the target firm introduces its corporate culture on its website, we count 1. If it introduces corporate mission on its website, we count 1. If the company has employee handbook with cultures of value, we count 1. If the company has ever trained their employees in cultures of value, we count 1. If the company has ever advertised its cultures in any social media, we count 1. The culture strength index is the sum of the five indicators. The definitions of other control variables are in Appendix A. We control for acquirer's industry and announcement year fixed effect. In parentheses are two-sided p-values based on standard errors adjusted for heteroskedasticity (White, 1980) and acquirer clustering (Petersen, 2009). ***, **, * stand for statistical significance at the 1%, 5%, and 10% levels, respectively.

LD × CULTURE_STRENGTH	−0.002*
	(0.061)
LD	−0.003
	(0.482)
CULTURE_STRENGTH	−0.002
	(0.584)
DEALSIZE	0.031
	(0.146)
PAYMENTSTOCK	0.099***
	(0.004)
DIVERSIFYING	−0.003
	(0.568)
HIGHTECH	−0.004
	(0.539)
SIZE	−0.0003
	(0.887)
LEVERAGE	−0.012***
	(0.001)
TQ	−0.001**
	(0.048)
GDP	−0.017*
	(0.091)
GD	0.004
	(0.272)
MD	0.004
	(0.234)
Industry	YES
Year	YES
Constant	0.116
	(0.111)
N	543
R-Squared	0.142

insignificant. More importantly, the linguistic distance measure is still significantly negatively related to the announcement return, mitigating the concerns that the result is driven by the potential social connections between the two firms.

3.4.4. How does LD evolve over time?

To examine whether linguistic distance matters more in early years, we partition the sample into deals before 2005 and deals after 2005. In the year 2005, The National Putonghua Promoting Office issued "Putonghua Propaganda Outline and Slogan" to further promote Putonghua. Thus, Putonghua has been more popular and more important in people's daily life since then.

We create a dummy variable (*A2005*) that equals one if the deal was announced in year 2005 and after, and zero otherwise. We re-run the main regression with the dummy variable and an interaction term (*LD* × *A2005*). The results are presented in Table 13. Linguistic distance is still significantly negatively related to the announcement return while the announcement return does not show

Table 12
The impact of social connection between bidder and target.

This table reports the OLS regression results of the social connection between director of bidder and target on the 5-day acquirer's CAR. A dummy variable (*DIR_SC*) equals one if the acquirer has any director from the target's location, and zero otherwise. The definitions of other control variables are in Appendix A. We control for acquirer's industry and announcement year fixed effect. In parentheses are two-sided p-values based on standard errors adjusted for heteroskedasticity (White, 1980) and acquirer clustering (Petersen, 2009). ***, **, * stand for statistical significance at the 1%, 5%, and 10% levels, respectively.

LD	−0.010***
	(0.001)
DIR_SC	0.007
	(0.242)
DEALSIZE	0.027
	(0.187)
PAYMENTSTOCK	0.101***
	(0.003)
DIVERSIFYING	−0.004
	(0.488)
HIGHTECH	−0.002
	(0.701)
SIZE	−0.0004
	(0.856)
LEVERAGE	−0.012***
	(0.001)
TQ	−0.001*
	(0.072)
GDP	−0.018*
	(0.074)
GD	0.004
	(0.263)
MD	0.004
	(0.185)
Industry	YES
Year	YES
Constant	0.114
	(0.117)
N	543
R-Squared	0.127

much difference before 2005 and after 2005. However, deals after 2005 are less negatively affected by the linguistic distance than deals before 2005. This result indicates linguistic background mattered more in earlier days when language friction was greater.

4. Conclusions

Understanding the role of culture in corporate decisions has been gaining increasing attention in recent years (Karolyi, 2016). Using the linguistic distance matrix published by "The Language Atlas of China", we examine the effect of linguistic distance on M&As in China.

Three main findings emerge. First, the linguistic distance between the acquirer and the target significantly and negatively affect the acquirer's abnormal return. The results are economically significant. Second, linguistic distance has a more pronounced effect in deals in which both the acquirer and the target are not from high-tech industries, or the acquirers are less likely to be proficient in Putonghua, or the acquirers are less surrounded by a linguistically diverse environment. Third, the acquirer's CEO dialect experience matters. If he has ever worked in a firm located in the target's language area, the acquirer's return is higher.

The findings are robust to different model specifications, institutional differences in local financial development, and after accounting for multicollinearity between linguistic and geographical distances and the social networks between acquirers and targets. Further analyses suggest that (1) when an investment bank is involved in a deal, the negative effect of the linguistic distance on abnormal return is less, or (2) when the post-merger cost is high, the impact of linguistic distance on abnormal return is amplified.

Table 13
The evolution of linguistic distanc.

This table reports the OLS regression results of *LD* in recent years on the 5-day acquirer's CAR. A dummy variable (*A2005*) equals one if the deal was announced in year 2005 and after, and zero otherwise. The definitions of other control variables are in Appendix A. We control for acquirer's industry and announcement year fixed effect. In parentheses are two-sided p-values based on standard errors adjusted for heteroskedasticity (White, 1980) and acquirer clustering (Petersen, 2009). ***, **, * stand for statistical significance at the 1%, 5%, and 10% levels, respectively.

LD × A2005	0.009**
	(0.010)
LD	−0.015***
	(0.000)
A2005	−0.017
	(0.113)
DEALSIZE	0.033
	(0.117)
PAYMENTSTOCK	0.095***
	(0.004)
DIVERSIFYING	−0.006
	(0.458)
HIGHTECH	−0.001
	(0.884)
SIZE	−0.0001
	(0.970)
LEVERAGE	−0.012***
	(0.001)
TQ	−0.001*
	(0.077)
GDP	−0.018*
	(0.077)
GD	0.003
	(0.379)
MD	0.004
	(0.237)
Industry	YES
Year	YES
Constant	0.121
	(0.101)
N	543
R-Squared	0.138

Appendix A. Definitions of major variables

Variable	Definition
CAR [−2, +2]	Acquirer five-day cumulative abnormal return (in percentage) calculated using the market model. The market model parameters are estimated using the return data for the period [−240, −41]. The market index is the CRSP value-weighted return.
LD	The linguistic distance between the acquirer and the target measured using the matrix defined by "The Language Atlas of China".
LD_DUMMY	Dummy variable: 1 if the *LD* is positive, and 0 if the *LD* is zero.
LD_i	Dummy variable: 1 if the *LD* equals i, and 0 otherwise. i ranges from 0 to 5.
SIZE	Log transformation of the book value of asset (in RMB million) at the end of the most recent fiscal year end prior to the announcement date.
TQ	The ratio of market value of assets over book value of assets measured at the end of the most recent fiscal year end prior to the announcement date.
LEVERAGE	Book value of long-term and short-term debt divided by book value of total assets at the end of the most recent fiscal year end prior to the announcement date.
BM	The ratio of book value of assets at the end of the most recent fiscal year end prior to the announcement date to the market capitalization 11 trading days prior to the announcement.

DEAL_VALUE	Value of the transaction (in RMB million).
DEALSIZE	Value of the transaction divided by the acquirer's market value of equity measured 11 trading days prior to the announcement.
DIVERSIFY	Dummy variable: 1 if acquirer and target do not share the same industry, and 0 otherwise.
PAYMENTSTOCK	Dummy variable: 1 if the deal is paid all or partially by stock, and 0 if the deal is paid with zero stock.
HIGHTECH	Dummy variable: 1 if both the acquirer and the target are from high-tech industries as defined in "high-tech industry categories", and 0 otherwise.
MD	The difference in level of marketization index between the acquirer and the target. The index is developed by Fan et al. (2010).
GD	The log form of the distance between the acquirer's city and the target's city plus one.
SOE	Dummy variable: 1 if the ultimate controller of the acquirer is a state-owned firm, and zero otherwise.
REFORM	Dummy variable: 1 if the acquirer has finished its reform of non-tradable shares prior to the announcement date, and 0 otherwise.
GDP	The log form of the GDP of the province in which the firm is located.
POLITICAL	Dummy variable: 1 if firm's CEO at the date of the announcement has any working experience in the government before, and 0 otherwise.
DUAL	Dummy variable: 1 if the firm's CEO at the date of the announcement is also the chairman of the board, and 0 otherwise.
TENURE	The number of years since the firm's CEO at the date of the announcement has been appointed the current position.
EDUCATION	The highest degree of education of the firm's CEO at the date of the announcement, range from 5 to 1 if the CEO's highest degree is a PhD, a Master, a Bachelor, an Associate College, or below, respectively.
AGE	The age of the CEO at the date of the announcement.

Appendix B. Linguistic distance matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) Northeastern Mandarin	0																
(2) Jiaoliao Mandarin	1	0															
(3) Beijing Mandarin	1	2	0							\							
(4) Jilu Mandarin	2	1	1	0													
(5) Zhongyuan Mandarin	3	3	2	1	0												
(6) Jianghuai Mandarin	4	2	3	3	1	0											
(7) Lanyin Mandarin	3	3	3	3	1	3	0										
(8) Southwestern Mandarin	3	3	3	3	1	1	2	0									
(9) Jin Dialect	3	3	2	2	1	2	2	2	0								
(10) Hui Dialect	4	3	4	4	4	2	4	3	4	0							
(11) Gan Dialect	4	3	4	4	4	1	4	1	4	1	0						
(12) Goetian	4	4	5	5	4	1	4	3	4	1	1	0					
(13) Xiang Dialect	5	3	4	4	4	3	4	1	4	3	1	2	0				
(14) Cantonese	5	5	5	5	5	4	5	2	5	3	3	3	3	0			
(15) Hakka	5	5	5	5	5	2	5	2	5	2	1	3	2	1	0		
(16) Min	5	5	5	5	5	3	5	3	5	3	2	2	3	2	2	0	
(17) Others	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	0
Average Distance	3.467	3.067	3.267	3.2	2.933	2.333	3.4	2.2	3.2	3	2.533	3.067	3.067	3.733	3.333	3.667	

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Appendix C. Mitigating multicollinearity between linguistic distance (*LD*) and geographic distance (*GD*)

This Appendix presents the results on the impact of *LD* on 5-day CAR after mitigating multicollinearity between *LD* and *GD*. In Panel A, we replace the *LD* with the residual from the regression of *LD* on *GD* (Step 1). We then include both the residual and GD in the regression of announcement return (Step 2). In Panel B, we conduct an orthogonal transformation of both *LD* and *GD* and use the transformed variables in the regression equation. The definitions of other control variables are in Appendix A. All the columns control for acquirer's industry and announcement year. In parentheses are two-sided p-values based on standard errors adjusted for heteroskedasticity (White, 1980) and acquirer clustering (Petersen, 2009). ***, **, * stand for statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Using residuals	
Step 1	LD
GD	0.939***
	(0.000)
Constant	−0.320***
	(0.000)
N	543
R-Squared	0.530
Step 2	CAR
RESIDUAL_LD	−0.010***
	(0.002)
GD	−0.006**
	(0.037)
DEALSIZE	0.029
	(0.172)
PAYMENTSTOCK	0.101***
	(0.003)
DIVERSIFYING	−0.004
	(0.525)
HIGHTECH	−0.002
	(0.691)
SIZE	−0.0001
	(0.975)
LEVERAGE	−0.011***
	(0.001)
TQ	−0.001*
	(0.067)
GDP	−0.017*
	(0.084)
MD	0.004
	(0.201)
Industry	YES
Year	YES
Constant	0.109
	(0.131)
N	543
R-Squared	0.125

Panel B: Using an orthogonal transformation	
LD_ORTHOG	−0.012***
	(0.002)
GD_ORTHOG	−0.008**
	(0.037)
DEALSIZE	0.029
	(0.172)
PAYMENTSTOCK	0.101***
	(0.003)
DIVERSIFYING	−0.004
	(0.525)
HIGHTECH	−0.002
	(0.691)
SIZE	−0.0001
	(0.975)
LEVERAGE	−0.011***
	(0.001)
TQ	−0.001*
	(0.067)
GDP	−0.017*
	(0.084)
MD	0.004
	(0.201)
Industry	YES
Year	YES
Constant	0.098
	(0.178)
N	543
R-Squared	0.125

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